Market Maker Revenues and Stock Market Liquidity

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Abstract

We use an 11-year panel of daily specialist revenues on individual NYSE stocks to explore the relationship between market-maker revenues and liquidity. If market makers suffer substantial trading losses, lenders may respond by increasing funding costs or reducing credit lines, and market makers should respond by reducing liquidity provision. The data indicate that when specialists in aggregate lose money on their inventories, market-wide effective spreads widen in the days or weeks that follow, even after controlling for stock returns, volatility, and volume. This suggests an important role for market-maker financial performance in explaining liquidity time-variation. Revenues at the specialist firm level explain liquidity changes in that firm's assigned stocks. Revenues at the individual stock level do not explain changes in individual stock liquidity, consistent with a financial constraints model with broadly diversified intermediaries. Aggregate specialist revenues are increasing in conditional return volatility, as is revenue volatility. Specialist margins (specialist revenue per dollar of trading volume) are essentially constant across stocks, implying limited scope for cross-subsidization.

1. Introduction

Liquidity is important for our understanding of how traders and institutions affect asset prices (Amihud, Mendelson, and Pedersen (2006)). Theoretical work by Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006), among others, postulates that limited market maker capital can explain various empirical features of asset market liquidity. Data limitations have hampered empirical work in this area, making it difficult to demonstrate strong links between liquidity supplier behavior and capital constraints. In this paper we use 11 years of New York Stock Exchange (NYSE) specialist trading revenue data to examine how market maker revenues impact daily stock market liquidity. The basic mechanism is simple: if market makers suffer substantial trading losses, lenders may respond by increasing funding costs or reducing credit lines. All else equal, market makers should respond to these constraints by reducing the amount of liquidity they are willing to provide.

Hendershott, Moulton, and Seasholes (2007) show that aggregate NYSE specialist positions are net long over 94 percent of the time. Specialists also have an affirmative obligation to buffer order flow, buying when others want to sell and vice versa. This means that specialists tend to lose money when the aggregate market declines. If these losses impose financial constraints on market makers, then liquidity will be worse immediately thereafter. Thus, market maker trading losses might be able to account for the well-known negative relationship between liquidity and lagged returns (see, for example, Chordia, Roll, and Subrahmanyam (2001), Chordia, Sarkar, and Subrahmanyam (2005), and Hameed, Kang, and Vishwanathan (2006)).

Our data cover only one market maker per stock – the specialist assigned by the NYSE to that stock – but that liquidity provider is probably the most important one, given the structural advantages that accrue to the specialist. In addition, specialist revenues may be good proxies for trading revenues earned by other competing liquidity suppliers, such as market-makers on regional exchanges, proprietary trading desks at various Wall Street firms, hedge funds following a market-making strategy, and so on. While we have no direct evidence that these other market makers have a long bias, an average long position might be optimal in the presence of an equity premium. In any case, all of these market-makers buffer order flow, so all are likely to lose money following a sharp price decline. Thus, it may be appropriate to think of our specialist revenue numbers as reflective of broader market-maker revenues.

Specialist trading revenues vary considerably over time. In fact, specialists in aggregate lose money on about 10% of the trading days during our sample, the average loss is about $4 million on these days, and these losses tend to cluster together in time. So there is ample scope for negative specialist revenues to force contractions in liquidity provision. Specialists almost always earn positive trading revenue on short-term roundtrip transactions, but are exposed to the possibility of losses on inventories held for longer periods. This suggests that the revenues associated with longer-term inventories could be better indicators of whether financial constraints are easing or tightening. When we decompose revenues into intraday vs. longer-term components, we find that revenues associated with inventories held overnight are indeed the ones that are associated with future liquidity. This overnight breakpoint dovetails nicely with our story, because anecdotal evidence indicates that lenders and risk managers are most likely to evaluate financing terms and position limits based on daily P&L and end-of-day balance sheets.

Because of the long bias in their aggregate position, specialists as a group tend to lose more money when the market falls. We already know that when the market falls, aggregate liquidity worsens. Putting these two facts together, we would expect to see in univariate regressions that liquidity worsens when specialists lose money. Given this collinearity, the empirical challenge is to separate the two variables and assess whether market maker revenues can account for the observed time-series predictability in liquidity. Fortunately, aggregate specialist trading revenues are not perfectly correlated with contemporaneous market returns, so it is possible to find times when specialists lose money without a corresponding market fall, or when specialists earn positive trading revenue in a declining market. When both variables appear in a predictive regression, specialist losses are associated with wider spreads next period. At daily horizons, market declines also have incremental explanatory power, but market returns are no longer significant at weekly horizons. So it appears that this proxy for financial constraints is able to completely explain weekly variation in aggregate liquidity, but is unable to completely account for higher-frequency liquidity squiggles.

The effects are strong at the aggregate level. However, if specialist financing constraints are the mechanism and specialist firms do not all lose money at the same time, the relationship should be present and in fact stronger at the specialist firm level. There should be a common component in liquidity for all stocks assigned to a particular specialist firm, and that firm's revenues should affect liquidity in those stocks. Coughenour and Saad (2004) demonstrate the

former; here we show that a specialist firm's trading revenues predict future liquidity in that firm's assigned stocks.

Finally, at the individual stock level, there is also substantial time-series variation in liquidity. But as long as individual equity markets are not segmented and market-makers are broadly diversified, market-maker losses that are confined to a single stock should not affect the market-maker's ability to provide liquidity in that stock. And that is exactly what we find. The financing constraints seem to be operating at the specialist firm level and at an aggregate market-wide level.

Because aggregate specialist revenues are important for liquidity, we investigate the sources of revenue variation through time. Aggregate return volatility turns out to matter most, and volatility has the biggest impact on the intraday component of revenues. Because this intraday component is really bid-ask spreads less losses to more informed traders, either spreads earned by specialists are wider in volatile markets, or specialists are better able to sidestep informed trades in volatile markets. Either way, it appears that specialist market power is greater when return variance is high.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 provides a general description of our data and sample. Section 4 shows the basic relation between aggregate market maker revenues and market liquidity. Section 5 looks at the specialist firm level; Section 6 examines individual stock liquidity and market maker revenues. Section 7 investigates the time series of market maker revenues and their volatility. Section 8 studies the cross section of individual stock market maker revenues and revenues per dollar traded. Section 9 concludes.

2. Related Literature

Most models of market liquidity focus on three types of trading costs: fixed, inventory, and information.[1] Theory focusing on funding costs (capital constraints) is more recent. Kyle and Xiong (2001) show how convergence traders (arbitrageurs) having decreasing risk aversion leads to correlated liquidations and higher volatility. Gromb and Vayanos (2002) study a model in

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[1] Kyle (1985) and Gloston and Milgrom (1985) examine the impact of private information. Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1981, 1983), and Grossman and Miller (1988) examine the impact of inventories.

which arbitrageurs face margin constraints and show how these arbitrageurs' liquidity provision benefits all investors. However, because the arbitrageurs cannot capture all of the benefits, they fail to take the socially optimal level of risk. Weill (2006) examines dynamic liquidity provision by market makers and shows that if they have access to sufficient capital, the market makers provide the socially optimal amount of liquidity, but if capital is insufficient or too costly then market makers will undersupply liquidity. Brunnermeier and Pedersen (2006) construct a model—along the lines of Grossman and Miller (1988)—that also links market makers' funding and market liquidity.[2]

Chordia, Roll, and Subrahmanyam (2001) are the first to show that volatility and negative returns reduce aggregate stock market liquidity. Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) examine the common component in liquidity changes across stocks. Coughenour and Saad (2004) study this further by showing that the co-movement in liquidity is stronger among stocks traded by the same NYSE specialist firm and this commonality is stronger for smaller specialist firms. Hameed, Kang, and Viswanathan (2006) examine the impact of negative returns on liquidity commonality and co-movement. Chordia, Sarkar, and Subrahmanyam (2005) study linkages between order flows, volatility, returns, and liquidity across the stock and bond markets.

Both liquidity supplier wealth and the amount of capital committed by liquidity suppliers play significant roles in the theoretical work on capital constraints and liquidity. This paper examines how market-maker firms' gains and losses, which should correlate with their wealth, impacts liquidity. Using specialist inventory positions, Hendershott, Moulton, and Seasholes (2007) show that the inventory (committed capital) channel is also important for aggregate liquidity.[3] They show that larger specialist inventories imply worse liquidity, and that specialists take on less inventory when liquidity worsens.

A number of papers examine the profitability of specialists. Hasbrouck and Sofianos (1993), decompose specialist profits over their trading horizon and find that most profits are due to their high frequency (short-term) trading strategies. Coughenour and Harris (2004) extend this

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[2] This effect is more severe if market makers face market-liquidity-reducing predation (Attari, Mello, and Ruckes (2005) and Brunnermeier and Pedersen (2005)).

[3] Naik and Yadav (2003) show that the contemporaneous relationship between government bond price changes and changes in market-maker inventories differs when market-maker inventories are very long or very short, but they do not directly examine liquidity.

econometrically and examine how the tick size change from 1/16 to \$0.01 impacts specialist profits. Panayides (2006) analyzes how specialists' trading, inventory, and profitability depend on their obligations under NYSE rules.

3. Data and Descriptive Statistics

Three data sets are used in our empirical work. CRSP is used to identify firms (permno), market capitalization, closing prices, returns, and trading volume. Market-wide returns are calculated as the market-capitalization weighted average across stocks. Internal NYSE data from the specialist summary file (SPETS) provide the specialist inventory position, specialist purchases, and specialist sales in shares and dollars for each stock each day from 1994 through 2004. The Trades and Quotes (TAQ) master file provides the CUSIP number that corresponds to the symbol in TAQ on each date and is used to match with the NCUSIP in the CRSP data.[4] We consider only common stocks (SHRCLS = 10 or 11 in CRSP), and we exclude stocks priced over \$500. We use only NYSE trades and quotes from TAQ to calculate liquidity measures.

For each stock each day, we measure the specialist's gross revenues from trading. These are gross revenues because we do not subtract any costs, such as salaries, fees, or technology investments, and they are gross trading revenues because we ignore other possible specialist revenue sources, mainly brokerage commissions charged to other floor participants.

Gross trading revenues (GTR) in stock i on day t are calculated as in Sofianos (1995) by marking to market the specialist's starting and ending inventories and adding the gross profits due to buys and sells:

$$GTR_{it} = (S_{it} - B_{it}) + (p_{it}I_{it} - p_{i,t-1}I_{i,t-1}),$$

where p_{it} is the share price of stock i at the end of day t, I_{it} is the specialist's inventory in shares of stock i at the end of day t, S_{it} is the total dollar value of stock i sold on day t, and B_{it} is the total dollar value of shares bought. For simplicity we suppress subscripts i in the discussion that follows.

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[4] The symbol in TAQ and ticker in CRSP match only 90% of time in our CUSIP matched sample, suggesting that using the TAQ master file to obtain CUSIPs is constructive.

To decompose these profits, begin by defining $\overline{p}_t^s$ as the specialist's average selling price on day t, with $\overline{p}_t^b$ the corresponding average buying price, and define s_t and b_t to be the shares sold and bought, respectively, on day t. Then:

$$S_t = s_t \, \overline{p}_t^s$$

$$B_t = b_t \, \overline{p}_t^b \,.$$

Now rewrite gross trading revenue as:

$$GTR_t = (s_t \overline{p}_t^s - b_t \overline{p}_t^b) + p_t(I_t - I_{t-1}) + I_{t-1}(p_t - p_{t-1})$$

and expand the first term in parentheses:

$$GTR_t = \min(s_t, b_t)(\overline{p}_t^s - \overline{p}_t^b) + \overline{p}_t^s(s_t - b_t)^+ - \overline{p}_t^b(b_t - s_t)^+ + p_t(I_t - I_{t-1}) + I_{t-1}(p_t - p_{t-1})\,.$$

Finally, using the fact that

$$I_t = I_{t-1} + (b_t - s_t)$$

we obtain:

$$GTR_t = \min(s_t, b_t)(\overline{p}_t^s - \overline{p}_t^b) + (p_t - \overline{p}_t^b)(b_t - s_t)^+ + (\overline{p}_t^s - p_t)(s_t - b_t)^+ + I_{t-1}(p_t - p_{t-1})$$

The first term of this equation captures the difference in buying and selling prices for all round-trip transactions that the specialist completes on day t, and we call this *realized* or *round-trip trading revenue RTR$_t$*:

$$RTR_t = \min(s_t, b_t)(\overline{p}_t^s - \overline{p}_t^b)\,.$$

The remaining terms are defined as inventory-related trading revenue *ITR$_t$*:

$$ITR_t = (p_t - \overline{p}_t^b)(b_t - s_t)^+ + (\overline{p}_t^s - p_t)(s_t - b_t)^+ + I_{t-1}(p_t - p_{t-1})\,.$$

The first two terms of *ITR* reflect the mark-to-market profits on day t's changes in inventory (either long or short), and the last term is the mark-to-market profit on the starting inventory position. Thus, we have decomposed daily specialist profits for each stock into:

$$GTR_t = RTR_t + ITR_t,$$

reflecting an intraday spread-related component and an multi-day inventory-related component. The weekly GTR, RTR, and ITR are summations of the respective daily variables over five trading days.

To calculate aggregate market maker revenues each day *GTR*, *RTR*, and *ITR* are summed across all the stocks in the sample. Specialist participation rates and the nature of specialist

trading change markedly when the minimum tick size changes from eighths to sixteenths on June 24, 1997 and from sixteenths to pennies on January 29, 2001.[5] Specialist participation also changes markedly at the beginning of 2003.[6] To adjust for these discontinuities, we calculate the time-series mean of daily specialist revenues in each of four regimes – one for each minimum tick, plus an additional breakpoint at January 1, 2003 – and adjust our aggregate revenue measures by the appropriate regime mean.

To measure liquidity at the market level, we construct a daily spread measure averaged across all stocks in the sample. Because specialists and floor brokers are sometimes willing to trade at prices within the quoted bid and ask, we use the effective spread rather than the quoted spread to measure liquidity. The effective spread is the difference between an estimate of the true value of the security (the midpoint of the bid and ask) and the actual transaction price.[7] For the kth trade in stock j on day t , the dollar effective spread (E_{jkt}) and the proportional effective spread (e_{jkt}) are defined as:

$$E_{jkt} = 2\, I_{jkt}\, (P_{jkt} - M_{jkt}),$$
$$e_{jkt} = 2\, I_{jkt}\, (P_{jkt} - M_{jkt})\, /\, M_{jkt}.$$

where I_{jkt} is an indicator variable that equals one for buyer-initiated trades and negative one for seller-initiated trades, P_{jkt} is the trade price, and M_{jkt} is the quote midpoint prevailing at the time of the trade. We follow the standard trade-signing approach of Lee and Ready (1991) and, due to reporting lags, the prevailing quote is taken to be the quote in effect five seconds prior to a trade for data up through 1998. After 1998, we use contemporaneous quotes to sign trades and calculate effective spreads (see Bessembinder (2003), for example). We calculate E_{jt} and e_{jt}, the mean dollar and proportional effective spreads for each stock each day, by averaging E_{jkt} or e_{jkt} using share volume weights, and we calculate the market-wide liquidity measures E_t and e_t as the cross-sectional mean of E_{jt} or e_{jt} using market cap weights. We also estimate a number of

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[5] Though the NYSE moves approximately 100 common stocks to decimals between September and December 2000 as part of its testing and roll-out plans, the vast majority of stocks make the switch on January 29, 2001.

[6] In early 2003, the NYSE and SEC begin to investigate the trading behavior of specialists, leading to criminal indictments of individual specialists and fines for specialist firms (Ip and Craig (2003)).

[7] Other liquidity measures such as quoted spreads give qualitatively similar results. Results in this paper also hold for each of the tick-size sub-periods (eighths, sixteenths, and decimals).

specifications at weekly frequencies. For those, we simply calculate an equally-weighted average of the five daily market-wide effective spreads.

[Insert Figure 1 Here]

Chordia, Roll, and Subrahmanyam (2001) and Jones (2005) document a downward trend in average effective spreads over the first half of our sample period. Figure 1 shows that effective spreads continue this narrowing trend over the rest of the sample, but the decline is interrupted by the 2000-2002 market decline and punctuated by sharp spread declines around the two minimum tick size reductions: from eighths to sixteenths in June 1997, and from sixteenths to pennies in January 2001. To deal with these non-stationarities, we focus on spreads relative to their average values in the recent past, defining the market-wide relative effective spread es_t as:

$$es_t = E_t - \tfrac{1}{5} \sum_{s=6}^{10} E_{t-s},$$

with an analogous definition for $espr_t$, the market-wide relative proportional effective spread.

Lags 6 through 10 are used for the moving average because many of our specifications predict future effective spreads using returns and volume at lags 1 through 5 as explanatory variables. Thus, to simplify the interpretation of the results we want to ensure that our effective spread measure is not affected by contemporaneous correlation between, say, spreads and returns.

To measure changes in volatility we estimate the asymmetric GARCH(1,1) model of Glosten, Jagannathan, and Runkle (1993) on daily or weekly aggregate log stock returns R_t:

$$h_t = \kappa + \delta\, h_{t-1} + \alpha\, u_{t-1}^2 + \phi\, u_{t-1}^2 I_{t-1},$$

where $u_t = R_t - \mu$ is distributed $N(0, h_t)$, and $I_{t-1} = 1$ if $u_{t-1} \geq 0$ and $I_{t-1} = 0$ otherwise. In order to match the treatment of effective spreads, we do not use h_t directly as an explanatory variable but instead define $vret_t$ as h_t less the average conditional variance h_t at lags 6 through 10. In some regressions we also include $uvret_t$, the unexpected volatility at time t, which is defined as $u_t^2 - h_t$.

To measure trading volume we use the logarithm aggregate daily or weekly change in dollar trading volume over the last five periods. We also measure the volatility of log trading volume

changes using a standard GARCH(1,1) model. As in the case of return variance, we define the explanatory variable $vvol_t$ as the conditional variance of volume at time t less the average conditional variance of volume at lags 6 through 10, and the unexpected volatility of trading volume $uvvol_t$ is defined analogously to $uvret_t$.

Table 1 contains summary statistics on the specialist revenue and other variables. Aggregate specialist revenues are fairly volatile, with a daily standard deviation of $5.685 million around the regime means and a weekly standard deviation of $15.484 million. RTR is much more highly correlated with contemporaneous GTR than is ITR (e.g., 0.878 vs. 0.439 at weekly frequencies), which indicates that variation in overall specialist revenues is mainly driven by variation in round-trip revenues. RTR is positively correlated with relative effective spreads, changes in trading volume, and increases in the conditional variance of returns. Interestingly, the two components of specialist revenue are virtually uncorrelated with each other contemporaneously, while ITR is strongly correlated with contemporaneous stock market returns (for daily observations, $\rho = 0.570$). The latter correlation makes sense given that aggregate specialist inventories are almost always net long, as documented in Hendershott, Moulton, and Seasholes (2007).

Specialist revenues also display an interesting persistence pattern. At short horizons, overall revenues are fairly persistent, with a daily GTR autocorrelation of 0.341. This persistence is completely gone at weekly levels. In fact, the weekly GTR autocorrelation is negative and statistically significant at -0.101. When revenues are decomposed into inventory and round-trip components, the daily persistence in GTR is driven by RTR, which has a daily autocorrelation of 0.447. The persistence in RTR also disappears at weekly horizons. While not the focus of the paper, this pattern in intraday revenues could reflect short-lived persistence in volume, adverse selection, and/or market power.

[Insert Table 1 Here]

4. Market Liquidity and Market Maker Revenues

The main empirical goal of the paper is to see if economic state variables related to financing constraints can account for the observed time-series variation in market liquidity. Our main innovation is the use of specialist revenues as a proxy for financial constraints faced by

intermediaries, but we also benchmark the findings by examining other possible mechanisms, such as the standard theoretical link between conditional volatility and market liquidity that is present in most microstructure models.

We start by simply regressing effective spreads at time t on *GTR* summed over the interval $[t - 5, t - 1]$. The results are in the first column of each panel of Table 2. Panels A and B examine dollar effective spreads at daily and weekly frequencies, while Panels C and D examine proportional effective spreads. In every case, aggregate specialist revenues do not seem to explain future market-wide liquidity changes at all. At first glance, this would seem to provide little support for a financing constraints story, because it is aggregate losses that would impair a market-maker's capital position and make it more difficult for an intermediary to finance its trading positions. However, specification (2) in the same table reveals that when gross trading revenues are partitioned into overnight ITR and intraday RTR, inventory revenues have a large negative effect on spreads, while the coefficient on RTR is of the opposite sign and only marginally significant.

[Insert Table 2 Here]

Ultimately, we focus on ITR because there are confounding effects between RTR and future spreads. When round-trip trading revenues are unusually high, spreads weakly tend to widen the next day or week. This positive relationship is probably unrelated to financing constraints. RTR is essentially the total dollar amount of effective spread earned on intraday round-trips by the specialist less the associated losses to informed traders. Thus, it is a realized or net spread. If these realized spread changes are persistent for whatever reason (say, for example, that specialist market power or the amount of intraday specialist trading is persistent), then the relationship between today's RTR and tomorrow's spread is fairly mechanical. If RTR and spreads both increase today, they are likely to both remain high tomorrow, and a higher RTR today ends up predicting a higher effective spread tomorrow.

In contrast, inventory-related revenues are not tied up with spreads in this way and are much easier to interpret. Here the effect goes in the right direction: when specialists make money on their inventories, market-wide spreads tend to narrow the next period. The effect seems fairly small economically: all else equal, a one standard deviation increase in ITR

narrows our aggregate proportional effective spread measure by 3.255 * -0.042 = 0.1 basis points on average the next day, compared to a daily standard deviation of 0.748 basis points for the spread measure itself. However, the statistical evidence is fairly compelling, as these two variables alone explain about 20% of the variance in the effective spread measure at daily forecast horizons.

Chordia, Roll, and Subrahmanyam (2000, 2001) show that when markets fall, liquidity dries up. The regression in specification (3) confirms that this effect is present and strong in this sample. When the relative proportional effective spread is regressed on stock returns over the past five days or weeks, the coefficient is always strongly significant, with a t-statistic of -4.44 in the weekly data (Panel D) and -9.76 for daily data (Panel C) and R-squared measures of around 23%. In economic terms, a negative stock market return of 2% over a given 5-day period (which is about one standard-deviation below the mean) increases the next day's effective spread measure by about 0.29 basis points, and a negative market return of 5% (again about one standard deviation below mean) over a given 5-week period tends to widen the effective spread measure by 0.47 basis points the next week. While it is possible that the wider proportional spread is due solely to a lower price in the denominator, the results in Panel A show that the market-wide dollar effective spread also widens in the days after a stock market decline, though this effect does not reliably extend to the regression at weekly frequencies in Panel B.

The remaining specifications explore various economic explanations for this relationship. Empirically, the question is whether any effect of lagged returns can be driven out by adding economically-motivated state variables to the regression. Specification (4) of Table 2 adds specialist revenue variables, which are proxies for market-maker financial constraints, as well as the conditional return variance from an asymmetric GARCH model, because most microstructure models find that spreads are an increasing function of return variances. We focus first on the results for dollar effective spreads in Panels A and B, because they are immune from the mechanical relationship that relates proportional spreads and the stock price level. Note that R^2 measures for dollar effective spread regressions tend to be lower for the same reason. At both daily and weekly frequencies, specialist revenues and the conditional return variance both predict dollar spreads in the expected direction, and these variables render lagged returns insignificant in predicting future liquidity. This is also true for regressions predicting proportional spreads at weekly frequencies (Panel D): lagged returns are driven out by specialist

revenues. At daily frequencies (Panel C), lagged returns have an incremental ability to predict proportional spreads over and above specialist revenues and conditional volatility, but the denominator effect is likely to be strongest at these shorter horizons. Even in this specification, however, it is worth noting that market-maker revenues continue to exhibit incremental explanatory power. When specialists lose money overall, both dollar and proportional spreads widen, even if the market is not falling at the same time.

The last specification in Table 2 adds lagged changes in aggregate trading volume over the past five days or five weeks, as well as the conditional variance of changes in trading volume. These are meant to be control variables. We do not have any clear priors on their sign, because the relationship between spreads and volume is ambiguous in most microstructure models. If volume goes up because there are more liquidity traders, we would expect liquidity to improve, e.g., Copeland and Galai (1983). If volume rises because there are more informed traders, as with the information events in Easley and O'Hara (1992), we might expect the opposite. Empirically, specification (5) reveals that increases in volume and increases in the variance of volume both tend to widen future spreads at daily horizons, but not at weekly horizons.[8] Even at daily horizons, the effect is modest, and more importantly, adding volume variables leaves other coefficient estimates virtually unchanged.

For robustness, we have also estimated a number of variants of these specifications. For example, in the reported specifications, the specialist revenue variables are at a disadvantage compared to volatility, as the volatility specification allows an asymmetric effect following stock price declines. But adding a kink to ITR at zero or partitioning ITR based on the market return does not affect the results at all. The reported results are not driven by any particular subsample: the results are present during each of the tick-size periods in our sample, and the results are present in generally rising and generally falling markets. The results also hold for quoted spreads as well as effective spreads.

4.1. A VAR as an alternative specification

Most of the variables in the regressions are calculated relative to recent means over the interval [t − 10, t − 6]. This is a kind of hybrid approach, as it is somewhere between working

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[8] See Lee, Mucklow, and Ready (1993) for intraday evidence that higher volume leads to higher subsequent spreads.

with levels and working with first differences. In this particular application, first differences are not appropriate, since there is no theoretical reason to believe that any of the variables here contain a unit root. Levels are not appropriate in the presence of apparent non-stationarity. While we are not aware of any econometric theory that directly addresses our approach, subtracting off recent means is a common approach in other areas of finance (cf. the relative T-bill yield, introduced by Campbell (1991) and now very common in the return predictability literature). The hybrid approach induces a modest amount of moving average behavior, which requires the use of autocorrelation-consistent standard errors. To ensure that the main results are not an artifact of this methodology, for robustness we use a somewhat more standard approach, constructing a vector autoregression to capture the joint dynamics of spreads, returns, and specialist revenues.

We estimate a daily VAR with 5 lags using detrended ITR, RTR, absolute market returns (*absret*), market returns (*retm*), and effective spreads, either dollar (*es*) or proportional (*espr*). Spreads are detrended using a piecewise linear trend within each tick size regime. Regime means are subtracted for other variables. Granger causality results are based on bivariate VARs with 5 lags and are reported in Table 3. The results generally reflect the univariate correlations discussed earlier. It is worth noting that ITR, absolute returns, and signed market returns all strongly Granger-cause changes in effective spreads, but we cannot reject the null that RTR does not Granger-cause innovations in spreads.

[Insert Table 3 Here]

The VAR allows us to examine impulse responses to orthogonalized shocks. The ordering of the variables is ITR, RTR, *absret, retm,* followed by the effective spread. This allows us to measure how a shock to ITR affects spreads in the future, and once this effect is taken into account, we can determine whether market returns orthogonal to ITR have any incremental ability to predict future spreads. The impulse response functions are displayed in Figure 2 and reflect the response of either dollar or proportional effective spreads over the next 25 trading days to a unit standard deviation orthogonalized shock to one of the five variables. Notice first that innovations to effective spreads are quite persistent, requiring a full month or so to return to its detrended mean.

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[Insert Figure 2 Here]

More interesting are the responses to shocks in the other variables. Shocks to ITR have strong and persistent effects on spreads. A one-standard deviation negative shock to ITR causes dollar spreads to widen by about 0.08 cents (0.2 basis points for proportional spreads). This is the biggest effect on spreads of any of the five variables. A volatility shock in the form of a large absolute return also causes spreads to widen, but its effect is smaller and less persistent. A negative market return does not affect dollar spreads, but proportional spreads are modestly affected for at least one month. The VARs provide a dynamic element that is not present in the regressions, but the results on predicting spreads are virtually identical.

Overall, the aggregate evidence strongly supports a role for financial constraints in shaping stock market liquidity. However, financial constraints should operate at the level of the financial intermediary rather than at the aggregate level, so we turn next to more disaggregated evidence to see if it too supports a capital constraint story.

5. Specialist firm revenues and liquidity in stocks assigned to the firm

If specialists are marginal liquidity suppliers, then a stock's liquidity should suffer if its specialist firm faces financing constraints. If financing constraints bind for all specialist firms at the same time, then we should indeed see all the effects at the aggregate level. However, if specialist firm revenues are imperfectly correlated, different specialist firms may face financing constraints at different times, and we should be able to find empirical support for the constraints hypothesis by identifying a relationship between specialist firm revenues and liquidity in that firm's assigned stocks, after controlling for aggregate effects.

At the end of our sample, there are only seven specialist firms, each with a broadly diversified list of assigned stocks. Facing little idiosyncratic risk, specialist firms are likely to earn revenues that are highly correlated with each other and with aggregate specialist revenues. However, early in the sample, there are more than 40 specialist firms, resulting in considerable cross-sectional dispersion in revenues and aiding identification.

To proceed, we disaggregate to the specialist firm level and create a panel with one observation for each specialist firm for each day or week. We calculate aggregate gross trading

revenues each period for each specialist firm (*gtrf*), which is decomposed into overnight inventory-related revenues (*itrf*) and intraday round-trip revenues (*rtrf*). A value-weighted effective spread measure is calculated each day or week for all the stocks assigned to a given specialist firm. We also calculate value-weighted returns (*retp*) on this portfolio of assigned stocks in excess of the aggregate market return, along with the associated conditional volatility (*vretp*) using an asymmetric GARCH model. We difference and demean these variables as in the aggregate analysis of Section 3. Pooled regressions are estimated, and Rogers standard errors are calculated which are robust to cross-sectional correlation.

[Insert Table 4 Here]

The results are in Table 4. Panels A and B analyze dollar effective spreads, at daily and weekly frequencies respectively. Panels C and D display results for proportional effective spreads. Specification (1) shows that, in contrast to earlier regressions at the aggregate level, specialist firm gross trading revenues are significant predictors of next day liquidity in that firm's assigned stocks. As discussed earlier, there could be confounding effects between intraday revenues (RTR) and future spreads, so we again decompose the specialist firm's daily revenues and focus on revenues that arise from overnight inventory (ITR). These effects in specification (2) are quite strong, with t-statistics ranging from 7.7 to 11.8 depending on the frequency and the spread measure.

We provide other intermediate specifications, but most relevant is specification (5), which predicts next-period effective spreads on the value-weighted portfolio of assigned stocks using specialist firm-level ITR and RTR, aggregate market returns and returns on the portfolio of assigned stocks, and conditional volatility on the assigned stocks. Firm-level trading revenues always predict effective spreads, regardless of the frequency or spread measure. For the dollar spread measure, the firm-level trading revenues drive out returns on the firm's stocks. This is not true for proportional spreads, but as we argued earlier, the presence of price in the denominator can mechanically cause returns to predict proportional spreads. Overall, we conclude that at the specialist firm level, there is strong evidence that firm trading revenues rather than idiosyncratic returns affect next period's spreads in a specialist firm's stocks, which

provides support for the hypothesis that intermediary-level financial performance affects liquidity.

6. Individual Stock Liquidity and Revenues

If time-variation in liquidity reflects financing constraints faced by intermediaries, the relationship between operating performance and liquidity should operate at the intermediary firm level. For the intermediaries being studied here, assuming internal capital markets are working correctly within the specialist firm, there should be no relationship between individual stock liquidity and specialist revenues in that stock. On the other hand, many alternative explanations imply such a relationship at the individual stock level. For example, if there is an agency problem within the specialist firm, the firm may choose to provide less trading capital to an individual specialist after a big loss. Perhaps a big loss is a sign that the information environment has changed, and market-makers worry more about adverse selection. Perhaps an individual specialist simply becomes more risk averse after he loses money in an individual stock. Each of these alternatives implies a relationship between specialist revenues and liquidity at the individual stock level, and we attempt to sort out these possible explanations using the full panel of specialist revenue and individual-stock liquidity.

Pooled regressions are estimated for a panel of all NYSE stocks during the 1994-2004 sample period. The dependent variable is the proportional effective spread during day or week t in stock i relative to its average value during the interval $[t–10, t–6]$, measured in basis points. This acts something like a fixed effect, in that the explanatory variables do not have to explain across-firm variation in average spread levels. Explanatory variables appear in pairs, with a firm-specific and market-wide version of each. There are aggregate and stock-specific inventory revenues (*itrm* and *itrs*), round-trip intraday revenues (*rtrm* and *rtrs*), lagged stock returns (*retm* and *rets*), where the own-stock return is the excess return over the market return, and conditional return variances (*vretm* and *vrets*). As before, revenues and returns are measured during the interval $[t–5, t–1]$, and each variance is the time $t–1$ forecast of the time t conditional return variance from a univariate asymmetric GARCH model, measured relative to the conditional variance during the interval $[t–10, t–6]$. We use Rogers standard errors to control for contemporaneous correlation in error terms (Peterson (2006)).

We start first by including just the specialist revenue variables. The results are in specification (1) of Table 5. We continue to focus on the revenues associated with overnight inventory, and here spreads are negatively associated with lagged aggregate and firm-specific ITR. The magnitude of the coefficient on firm-specific ITR (*itrs*) is much bigger than the coefficient on *itrm*: using the daily regression results and holding other explanatory variables at their unconditional means, a 3% decline in a stock over a one-week period (which is about one standard deviation) implies that the effective spread measure widens by about 15 basis points. It is hard to attribute this result to market-maker financial constraints unless capital allocation to market-making is segmented at the individual stock level, which seems unlikely given that specialist firms and other liquidity providers make markets in many different stocks and are thus broadly diversified.

What accounts for the individual-stock revenue results? Specification (2) includes just lagged aggregate and firm-specific returns, and finds an extremely strong statistical relationship between lagged own returns and future liquidity, with t-statistics that are over 60. Thus perhaps the results for *itrs* in specification (1) again reflect the fact that specialists tend to be net long, resulting in a large positive correlation between firm-specific returns and firm-specific inventory revenues. When we include lagged returns and lagged revenues together in specification (3), we find that the aggregate inventory revenue variable *itrm* still matters, but the individual stock revenue variables are no longer significant in the daily data. In the weekly data, the coefficient on firm-specific inventory revenue *itrs* actually switches sign, possibly due to collinearity between the individual excess stock returns and the individual stock revenues. The results for own-stock revenue variables are good news for our story. If the operative mechanism is intermediary financial constraints, this mechanism should apply at the broad specialist firm or intermediary level, not the individual stock level, and that is what we find.

Of course, this leaves unanswered the question of why own lagged returns affect own stock liquidity. Part of the explanation is the denominator effect from using proportional effective spreads. Another hypothesis is that conditional volatility increases following a large price drop, and effective spreads could be widening to reflect that additional volatility. Specification (4) adds market-wide and individual-stock conditional variances. Both variables have the right sign.

Increases in conditional volatility lead to wider bid-ask spreads, and both market-wide and individual-firm volatilities are significant in the daily data. While conditional variances are statistically significant, they do almost nothing to any of the other coefficients.

Examining the impact of market maker revenues on liquidity at the market and individual stock levels confirms that the changes in liquidity are driven by more aggregated specialist revenues, not idiosyncratic individual stock revenues. This finding maps directly into the capital constraints story, so, in some ways, our main task is complete at this point. However, if we want a complete understanding of the interrelationships between liquidity and specialist revenue, we need to understand as thoroughly as possible what causes specialists to lose money, and that is the topic of the next two sections.

7. The Determinants of the Mean and Volatility of Specialist Revenues

Understanding market maker revenues involves examining these revenues in both the cross section and time series. Given that the capital constraints story is primarily focused on the time-series relationship between market maker revenues and liquidity, we begin our study of revenues in the time series. To investigate this, we run time series regressions using daily or weekly observations. The first set of regressions focuses on the first moment of market-maker revenues. The dependent variable is specialist gross trading revenues (*GTR*) or one of its two components: inventory-related trading revenues (*ITR*) or round-trip intraday trading revenues (*RTR*), each measured at time t. Explanatory variables include first and second moments of returns and trading volume, with each variable measured using information available at time $t - 1$. To be more precise, right-hand side variables consist of log value-weighted market returns in percent (*ret*), and log changes in aggregate trading volume (*vol*), each measured over the time interval [$t - 5, t - 1$], the time $t - 1$ forecast of the time t return variance from an asymmetric GARCH model (*vret*) and the unexpected realized return variance at time t (*uvret*), along with analogous variables for the variance of volume changes (*vvol* and *uvvol*). As before, specialist revenues are measured relative to the mean of the relevant tick-size regime, and conditional variances are measured as changes from their average values during the interval [$t - 10, t - 6$]. Inference is conducted using Newey-West standard errors with 10 lags.

Table 6 Panel A has the results for daily observations; results for weekly observations are in Panel B. Specialist revenues, and especially intraday round-trip revenues RTR, tend to be higher

if volume has risen over the past five periods. Volume is quite persistent, so higher volume in the recent past means higher volume today on average, on which the specialist tends to earn more revenue.

[Insert Table 6 Here]

The most robust results are for the variance of returns. When conditional variance is high, overall specialist revenue is high, and this result is driven by RTR, which itself reflects net spread revenues realized by the specialist over the course of the trading day. It is not surprising that spreads should be positively correlated with the conditional variance of returns; this is a feature of virtually every microstructure model. But RTR represents spreads net of losses to informed traders, and these are increasing in the conditional variance of returns. This result would not arise in a microstructure model with perfectly competitive intermediaries. Specialist market power could increase in more volatile markets, perhaps because communication lags are relatively more important in fast markets, giving the specialist a greater last mover advantage. Alternatively, this result could arise if intermediaries are risk averse or face financial constraints that lead to risk averse behavior.

To try to separate these two explanations, we examine the riskiness of the specialist revenue stream. The time-series regressions are virtually identical except for the dependent variable, which now is the standard deviation of daily aggregate specialist revenues during week t, or the standard deviation of daily ITR or RTR. The results are in Table 7, and they indicate strongly that specialist revenue volatility is increasing in the conditional variance of returns. In fact, ITR volatility and RTR volatility are both higher when return variance goes up. Thus, there is support for the hypothesis that at least some of the additional specialist revenue in volatile markets represents compensation for additional risk.

[Insert Table 7 Here]

8. The Cross Section of the Mean and Volatility of Revenues and Revenue Margins

Our last inquiry focuses on the variation in specialist revenues across stocks, in order to determine where specialists (and potentially other intermediaries as well) face the biggest risks and the biggest rewards. There has been some discussion in the literature about whether the specialist revenue from trading the most active stocks helps to subsidize market-making in less active stocks (Cao, Choe, and Hatheway (1997) and Huang and Liu (2003)). Our data can shed light on this particular question. The cross-sectional distribution of specialist revenue is also potentially important in understanding market-maker financial constraints. For instance, if only a few stocks account for the vast majority of specialist revenues, then specialist losses in these pivotal stocks may exert strong cross-effects on the liquidity of other stocks.

Our empirical analysis attempts to account for both the first and second moment of specialist revenues, measured in dollars and as a fraction of specialist trading volume in that stock (which we sometimes call the specialist's operating margin). We also look at the cross-sectional determinants of the two revenue components: inventory-related revenues ITR and revenues from intraday round-trips RTR. A Fama-MacBeth approach is used: cross-sectional regressions are estimated for each month t, and we report the time-series average of the resulting coefficients and conduct inference assuming independence across months. Stock characteristics from the previous month include the log market cap (*size*), average daily turnover (*turn*), the inverse of the month-end share price (*invprc*), the log return during the month in percent (*rets*), the average daily log changes in dollar volume during the month (*vols*), and the end-of-month t−1 forecast of the individual stock return variance on the first day of month t using an asymmetric GARCH model (*vrets*), along with an analogous variable related to the variance of volume changes (*vvols*) using a symmetric GARCH model. Conditional variances are measured as changes from their average values during the interval [t−10, t−6].

The results are in Table 8. Specialists generate more trading revenue in large stocks, active stocks, low-priced stocks, volatile stocks, and stocks with more variable trading volume. Most of these results are quite intuitive. For example, more trading means more revenue, a faster market (more volatility) gives the specialist a bigger advantage over other participants, and a low share price means the minimum tick is more likely to bind, with larger profits to liquidity providers. These cross-sectional relationships are all driven by intraday round-trip trading revenues.

In contrast to specialist revenues, when we look at specialist margins, defined here as specialist trading revenue per dollar of specialist trading volume, it is striking that none of these cross-sectional regularities are reliably present. In fact, we cannot reject the hypothesis that specialist margins are on average constant across stocks. This is a striking result, because the null hypothesis, if true, means that specialists do not earn negative revenues on average on any particular subset of stocks. Cross-subsidization may still be taking place, but these results indicate that specialist firms are, at most, using revenues from active stocks to subsidize the fixed costs of making a market in less active stocks. Put another way, if there are no fixed costs then we find no evidence of cross-subsidization. To the extent that technology lowers these fixed costs, e.g., through algorithmic liquidity supply, then the arguments for encouraging cross-subsidization at the NYSE appear weak.

Even though specialist margins do not differ much across stocks, margin risk does vary considerably. For example, specialist margins are more volatile in small stocks, high-priced stocks, and stocks where trading volume is more variable. These results are also fairly intuitive. For instance, information asymmetries are generally more severe in small-cap stocks, and spreads tend to be wider. Specialists earn bigger spreads in these stocks but may ultimately lose them if the counterparty turns out to be informed. In low-priced stocks, the minimum tick enforces a minimum spread and thus a fairly certain stream of revenues.

In fact, these kinds of revenue and revenue volatility results may be most valuable because they provide some insight into the risk management considerations at market-making firms. Regressions like these are probably being used by risk managers at specialist firms, who may in turn influence the cross-sectional allocation of specialist capital, perhaps thereby affecting the cross-section and time-series of liquidity. The influence of revenue volatility thus seems like it is worthy of additional study in future work.

9. Conclusion

In this paper, we use an 11-year panel of daily specialist revenues on individual NYSE stocks to explore the relationship between market-maker revenue and liquidity. At the aggregate level and at the specialist firm, it turns out that when specialists lose money on their inventories, effective spreads are significantly wider in the days or weeks that follow. When we run a horse race between inventory-related specialist revenues, market returns, and conditional return volatility at the aggregate market level, we find that both revenues and volatility have incremental predictive power for future liquidity, and in most specifications market returns no longer have incremental predictive power. This suggests that market-maker financial constraints can help us understand time-variation in liquidity, while also acknowledging the traditional mechanisms of microstructure theory that link price volatility and liquidity.

When we look at individual stocks, we find that own-stock specialist revenues do not explain changes in individual stock liquidity. Only aggregate specialist revenues or specialist firm revenues can predict future liquidity, which is precisely what we would expect of a financial constraints model with broadly diversified intermediaries.

We also investigate the variation in the level and risk of specialist revenues, both over time and across stocks. The main time-series result is that aggregate specialist revenues are increasing in conditional volatility. This effect is driven by intraday round-trip trades, suggesting that the specialist's structural advantage is more valuable in volatile markets. But this higher average reward comes with higher risk, as aggregate revenue volatility is also greater in volatile markets. Specialist revenues are highest for large stocks, active stocks, low-priced stocks, volatile stocks, and stocks with more variable trading volume. However, the main cross-sectional result is that specialist margins (specialist revenue per dollar of trading volume) are essentially constant across stocks, implying that if there are no fixed costs then there is no cross-subsidization

But puzzles do remain. The most puzzling result is at the specialist firm level, where specialist firm revenues do not drive out the relationship between spreads and lagged market returns. It could be that there are other broadly diversified firms or funds who are also marginal liquidity providers, in which case liquidity is affected not just by the specialist firm's revenues but also by broader market-wide state variables. Unfortunately, we do not have direct evidence to bring to bear on this issue.

It is also interesting to note the strong relationship between individual stock liquidity and lagged individual stock returns. This does not bear directly on the financial constraints hypothesis, but the effect is so strong that it warrants future work. We suspect that the information environment changes, with liquidity providers suffering greater losses to informed traders following a share price decline, and we are currently gathering price impact data to assess this explanation.

Ultimately, our revenue measures are noisy instruments for the bite of financial constraints. Even more useful would be direct evidence on changes in collateral requirements, credit limits, or financing costs imposed by lenders in response to shocks. Unfortunately, these are not readily available to us. However, we are currently looking at specialist consolidation in the late 1990's. In 1994, at the beginning of our sample period, there were 41 specialist firms. In 2004, at the end of our sample period, there were only 7. Many of these mergers were undertaken explicitly to shore up market maker capital. If small specialist firms faced fairly onerous constraints just prior to being taken over, such mergers could be useful instruments for an even better identification of financing constraints.

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Table 1. Summary time-series correlations and statistics. The sample extends from 1994 through 2004. Variables related to specialist revenue include aggregate gross trading revenues *gtr* decomposed into inventory-related revenues *itr* and round-trip revenues *rtr*, all measured in millions of dollars. Other explanatory variables include log value-weighted market returns in percent (*ret*), the change in log aggregate trading volume (*vol*), the value-weighted effective spread measured in basis points (*espr*) and in cents (*es*), as well as the time t–1 forecast of the time t return variance from an asymmetric GARCH model (*vret*) and a similar forecast of the variance of volume changes (*vvol*) from a symmetric GARCH model. Variables ending in 1 are lagged one period. Specialist revenues are measured relative to the mean of the relevant tick-size regime, and variances are measured as changes from their average values during the time interval $[t–10, t–6]$. Standard errors under the null of no correlation are 0.019 in Panel A and 0.042 in Panel B. Correlations that are statistically different from zero at the 5% level are in bold.

	gtr	*itr*	*rtr*	*gtr1*	*itr1*	*rtr1*	*ret*	*ret1*	*vret*	*vvol*	*vol*	*espr*	*es*	std. dev.
					Panel A: correlation matrix, variables measured daily									
gtr	1	**0.578**	**0.820**	**0.341**	-0.023	**0.434**	**0.311**	-0.014	**0.099**	-0.022	0.011	**0.046**	0.034	5.685
itr		1	0.007	**0.103**	0.009	**0.120**	**0.570**	0.034	0.020	-0.011	**-0.110**	**-0.145**	**-0.087**	3.255
rtr			1	**0.345**	-0.034	**0.447**	-0.018	**-0.041**	**0.107**	-0.020	**0.090**	**0.158**	**0.103**	4.639
gtr1				1	**0.578**	**0.820**	**0.045**	**0.311**	-0.021	-0.009	**-0.109**	**-0.108**	**-0.085**	5.686
itr1					1	0.007	0.035	**0.570**	**-0.210**	0.034	-0.028	**-0.275**	**-0.172**	3.256
rtr1						1	0.031	-0.018	**0.121**	-0.035	**-0.114**	**0.060**	0.017	4.640
ret							1	0.028	**0.059**	-0.012	**0.043**	**-0.122**	**-0.047**	1.084
ret1								1	**-0.193**	0.018	**-0.079**	**-0.214**	**-0.089**	1.084
vret									1	0.009	-0.015	**0.500**	**0.251**	0.815
vvol										1	**0.213**	0.033	0.031	0.078
vol											1	**0.048**	**0.063**	0.203
espr												1	**0.768**	0.748
es													1	0.425
					Panel B: correlation matrix, variables measured weekly									
	gtr	*itr*	*rtr*	*gtr1*	*itr1*	*rtr1*	*ret*	*ret1*	*vret*	*vvol*	*vol*	*espr*	*es*	std. dev.
gtr	1	**0.439**	**0.878**	**-0.101**	**-0.139**	-0.039	**0.221**	**-0.086**	**0.146**	0.027	-0.013	0.071	0.060	15.484
itr		1	-0.043	-0.033	**0.177**	**-0.131**	**0.584**	0.052	0.006	-0.006	**-0.228**	**-0.314**	**-0.266**	7.405
rtr			1	**-0.095**	**-0.249**	0.026	-0.065	**-0.123**	**0.159**	0.033	**0.107**	**0.246**	**0.209**	13.924
gtr1				1	**0.439**	**0.878**	0.018	**0.221**	0.070	0.003	**-0.099**	0.005	0.030	15.498
itr1					1	-0.043	-0.063	**0.584**	**-0.297**	-0.021	0.077	**-0.322**	**-0.203**	7.411
rtr1						1	0.054	-0.065	**0.235**	0.014	**-0.151**	**0.177**	**0.142**	13.934
ret							1	**-0.088**	**0.117**	0.002	-0.073	**-0.116**	-0.049	2.374
ret1								1	**-0.253**	-0.033	-0.032	**-0.200**	-0.027	2.376
vret									1	0.055	-0.084	**0.500**	**0.247**	6.384
vvol										1	**0.118**	**0.092**	**0.086**	0.029
vol											1	0.054	**0.088**	0.152
espr												1	**0.769**	1.017
es													1	0.416

Table 2. Aggregate specialist revenues and future market liquidity. Time-series regressions 1994-2004. The dependent variable is the value-weighted effective spread during day or week *t* relative to its average value during the interval [*t*–10, *t*–6], measured in cents (Panels A and B) or in basis points (Panels C and D). Explanatory variables related to specialist revenue include aggregate gross trading revenues *gtr* during the interval [*t*–5, *t*–1] decomposed into inventory-related revenues *itr* and round-trip revenues *rtr*, all measured in millions of dollars. Other time *t*–1 explanatory variables include the log 5-period value-weighted market return in percent (*retm*), the 5-period log change in aggregate trading volume (*vol*), and the time *t*–1 forecast of the time *t* return variance from an asymmetric GARCH model (*vretm*) and a similar forecast of the variance of volume (*vvol*). Specialist revenues are measured relative to the mean of the relevant tick-size regime, and variances are measured as changes from their average values during the interval [*t*–10, *t*–6]. T-statistics are based on Newey-West standard errors with 10 lags.

	Panel A: Dollar spreads, regressions at daily frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.016	-1.29	-0.016	-1.37	-0.010	-0.83	-0.017	-1.54	-0.029	-2.47
gtr	-0.002	-1.89								
itr			-0.012	-6.17			-0.009	-3.33	-0.008	-3.03
rtr			0.001	1.96			0.000	0.59	0.000	0.45
retm					-0.028	-4.44	0.005	0.72	0.004	0.59
vretm							0.104	3.25	0.100	3.26
vol									0.147	2.42
vvol									0.285	3.68
R^2	0.53%		5.28%		2.64%		8.17%		8.87%	

	Panel B: Dollar spreads, regressions at weekly frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.080	-2.04	-0.082	-2.2	-0.073	-1.83	-0.096	-2.57	-0.142	-3.44
gtr	0.000	-0.24								
itr			-0.007	-5.29			-0.007	-4.43	-0.006	-4.39
rtr			0.000	0.3			0.000	-0.04	0.000	-0.12
retm					-0.007	-0.86	0.015	1.55	0.013	1.48
vretm							0.015	2.13	0.013	1.83
vol									0.398	2.76
vvol									1.826	2.20
R^2	0.05%		11.77%		0.72%		15.51%		18.58%	

Table 2 (continued).

Panel C: Percentage spreads, regressions at daily frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.043	-1.57	-0.043	-1.83	-0.013	-0.58	-0.030	-1.53	-0.052	-2.4
gtr	-0.006	-1.84								
itr			-0.042	-8.78			-0.020	-4.65	-0.019	-4.34
rtr			0.005	2.26			0.001	0.91	0.001	0.79
retm					-0.146	-9.76	-0.062	-5.39	-0.063	-5.64
vretm							0.278	5.03	0.272	5.08
vol									0.237	2.64
vvol									0.503	3.19
R^2	1.8%		19.7%		22.4%		33.9%		34.6%	

Panel D: Percentage spreads, regressions at weekly frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.220	-2.2	-0.228	-2.54	-0.129	-1.34	-0.189	-2.24	-0.242	-2.64
gtr	-0.002	-0.45								
itr			-0.025	-5.74			-0.017	-4.95	-0.017	-4.83
rtr			0.001	0.17			-0.001	-0.38	-0.001	-0.39
retm					-0.095	-4.44	-0.038	-1.65	-0.038	-1.72
vretm							0.045	2.64	0.044	2.65
vol									0.200	0.72
vvol									2.112	1.31
R^2	0.3%		25.0%		22.9%		39.1%		39.4%	

Table 3. Granger causality tests. The vector autoregression has 5 daily lags and the following variables: specialist overnight inventory-related revenues (*itr*), specialist intraday round-trip revenues (*rtr*), the absolute market return (*absret*), the log value-weighted market return (*retm*), and the value-weighted effective spread, measured in cents (*es*) or in basis points (*espr*). Effective spreads are detrended with a linear time trend within each tick-size regime, and specialist revenues are detrended by subtracting the mean of the relevant tick-size regime.

Null hypothesis:	Dollar effective spreads		Proportional effective spreads	
	F-statistic	p-value	F-statistic	p-value
RTR does not Granger Cause ITR	13.5121	0.0000	13.5121	0.0000
ITR does not Granger Cause RTR	44.5714	0.0000	44.5714	0.0000
ABSRET does not Granger Cause ITR	1.7724	0.1151	1.7724	0.1151
ITR does not Granger Cause ABSRET	14.8700	0.0000	14.8700	0.0000
RETM does not Granger Cause ITR	2.0635	0.0671	2.0635	0.0671
ITR does not Granger Cause RETM	1.5106	0.1831	1.5106	0.1831
ES/ESPR does not Granger Cause ITR	1.3099	0.2567	1.9725	0.0796
ITR does not Granger Cause ES/ESPR	23.0416	0.0000	58.4455	0.0000
ABSRET does not Granger Cause RTR	7.8005	0.0000	7.8005	0.0000
RTR does not Granger Cause ABSRET	2.0569	0.0679	2.0569	0.0679
RETM does not Granger Cause RTR	3.5206	0.0036	3.5206	0.0036
RTR does not Granger Cause RETM	1.2117	0.3009	1.2117	0.3009
ES/ESPR does not Granger Cause RTR	7.1598	0.0000	12.4757	0.0000
RTR does not Granger Cause ES/ESPR	0.9763	0.4307	1.5293	0.1772
RETM does not Granger Cause ABSRET	34.3424	0.0000	34.3424	0.0000
ABSRET does not Granger Cause RETM	0.9349	0.4571	0.9349	0.4571
ES/ESPR does not Granger Cause ABSRET	1.9011	0.0909	5.9264	0.0000
ABSRET does not Granger Cause ES/ESPR	15.7772	0.0000	22.0791	0.0000
ES/ESPR does not Granger Cause RETM	1.4283	0.2107	5.3306	0.0001
RETM does not Granger Cause ES/ESPR	7.5631	0.0000	44.9906	0.0000

Table 4. Specialist firm revenues and future liquidity. Pooled regressions 1994-2004; the unit of observation is a specialist firm for a given day or week. The dependent variable is the value-weighted effective spread on the portfolio of stocks assigned to a given specialist firm during day or week t relative to its average value during the interval $[t–10, t–6]$, measured in cents (Panels A and B) or in basis points (Panels C and D). Explanatory variables include the specialist firm's gross trading revenues $gtrf$ during the interval $[t–5, t–1]$ decomposed into inventory-related revenues $itrf$ and round-trip revenues $rtrf$, all measured in millions of dollars. Other time $t–1$ explanatory variables include the log 5-period value-weighted market return in percent ($retm$), the excess return over the market return on the portfolio of stocks assigned to the specialist firm ($retp$), and the time $t–1$ forecast of the time t variance of $retp$ from an asymmetric GARCH model ($vretp$). Specialist revenues are demeaned in each tick-size regime, and variances are measured as changes from their average values during the interval $[t–10, t–6]$. T-statistics are based on Rogers standard errors that are robust to cross-sectional correlation.

Panel A: Dollar spreads, regressions at daily frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.012	-1.73	-0.012	-1.76	-0.004	-0.50	-0.005	-0.64	-0.005	-0.71
gtrf	-0.005	-2.89								
itrf			-0.061	-7.70			-0.041	-5.98	-0.041	-5.98
rtrf			0.005	3.16			0.003	2.37	0.003	2.31
retp					0.000	0.09	0.001	0.29	0.002	0.82
retm					-0.032	-6.60	-0.029	-5.94	-0.028	-6.03
vretp									0.005	1.63
R^2	0.01%		0.15%		0.35%		0.42%		0.43%	

Panel B: Dollar spreads, regressions at weekly frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.066	-5.55	-0.066	-5.70	-0.054	-4.54	-0.058	-4.97	-0.066	-5.65
gtrf	0.000	0.12								
itrf			-0.029	-8.25			-0.026	-7.90	-0.025	-7.69
rtrf			0.003	2.72			0.003	2.44	0.003	2.33
retp					0.002	0.89	0.002	1.08	0.005	1.86
retm					-0.009	-3.44	-0.007	-2.57	-0.004	-1.22
vretp									0.024	2.12
R^2	0.00%		0.70%		0.40%		0.93%		1.74%	

Table 4 (continued).

	Panel C: Percentage spreads, regressions at daily frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.048	-2.20	-0.048	-2.25	0.052	2.54	0.051	2.48	0.039	1.98
gtrf	-0.017	-3.06								
itrf			-0.216	-10.91			-0.056	-3.86	-0.053	-3.73
rtrf			0.019	5.63			0.008	2.98	0.006	2.37
retp					-0.204	-13.06	-0.204	-12.99	-0.164	-18.02
retm					-0.245	-18.54	-0.241	-18.12	-0.222	-17.87
vretp									0.124	5.57
R^2	0.0%		0.3%		4.6%		4.7%		5.6%	

	Panel D: Percentage spreads, regressions at weekly frequencies									
	(1)		(2)		(3)		(4)		(5)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	-0.257	-5.55	-0.259	-5.74	0.160	3.92	0.152	3.72	0.107	2.79
gtrf	0.000	-0.04								
itrf			-0.135	-11.80			-0.048	-5.50	-0.040	-4.96
rtrf			0.013	5.29			0.009	3.07	0.008	2.89
retp					-0.181	-18.26	-0.181	-18.35	-0.166	-18.41
retm					-0.195	-20.06	-0.190	-19.51	-0.170	-17.75
vretp									0.152	7.25
R^2	0.0%		1.5%		20.8%		21.0%		24.2%	

Table 5. Predictors of individual stock spreads. Pooled regressions 1994-2004. The dependent variable is the effective spread during day or week t in stock i relative to its average value during the interval $[t–10, t–6]$, measured in basis points. Explanatory variables related to specialist revenue include aggregate and stock-specific inventory-related revenues *itrm* and *itrs*, respectively, and round-trip revenues *rtrm* and *rtrs*, all measured during the interval $[t–5, t–1]$ in millions of dollars. Other time $t–1$ explanatory variables include the log 5-period value-weighted market return (*retm*) and the individual stock return (*rets*) in excess of the market return, both in percent, and the time $t–1$ forecast of the time t market return variance from an asymmetric GARCH model (*vretm*) and a similar forecast of individual stock return variance (*vrets*). Specialist revenues are measured relative to the mean of the relevant tick-size regime, and variances are measured as changes from their average values during the interval $[t–10, t–6]$. Rogers standard errors are in parentheses and are robust to cross-sectional correlation; significance at the 5% or 1% level is denoted by one or two asterisks, respectively.

	Panel A: Daily observations					Panel B: Weekly observations			
	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
Intercept	0.049	0.098 **	0.074 *	0.056	Intercept	0.076	0.217 **	0.142 *	0.105
	(0.036)	(0.034)	(0.032)	(0.031)		(0.083)	(0.074)	(0.072)	(0.068)
itrm	-0.117 **		-0.057 **	-0.043 **	itrm	-0.083 **		-0.031 **	-0.028 **
	(0.009)		(0.008)	(0.008)		(0.005)		(0.004)	(0.004)
itrs	-4.996 **		-0.154	0.054	itrs	-2.743 **		1.727 **	2.627 **
	(0.315)		(0.171)	(0.173)		(0.209)		(0.194)	(0.234)
rtrm	0.015 **		0.010 **	0.004	rtrm	0.001		0.009 **	0.007 *
	(0.004)		(0.003)	(0.003)		(0.004)		(0.003)	(0.003)
rtrs	0.234 **		-0.006	-0.021	rtrs	0.075 **		-0.301 **	-0.337 **
	(0.026)		(0.023)	(0.023)		(0.027)		(0.061)	(0.063)
rets		-0.547 **	-0.544 **	-0.523 **	rets		-0.546 **	-0.545 **	-0.489 **
		(0.008)	(0.008)	(0.008)			(0.008)	(0.008)	(0.007)
retm		-0.529 **	-0.430 **	-0.325 **	retm		-0.429 **	-0.370 **	-0.335 **
		(0.022)	(0.021)	(0.020)			(0.017)	(0.017)	(0.016)
vretm				0.660 **	vretm				0.135 **
				(0.079)					(0.009)
vrets				0.039 **	vrets				0.108
				(0.005)					(0.108)
R^2	0.1%	1.3%	1.3%	1.4%	R^2	0.6%	10.7%	10.8%	12.5%

Table 6. Determinants of aggregate specialist revenues. Time-series regressions 1994-2004. The dependent variable is either aggregate gross trading revenues *gtr* ($millions) during a given day or week *t*, or one of two components: inventory-related revenues *itr* or round-trip revenues *rtr*. Explanatory variables are all measured at time $t-1$ and include log value-weighted market returns in percent (*ret*), and log changes in aggregate trading volume (*vol*), each measured over the last 5 periods, the time $t-1$ forecast of the time *t* return variance from an asymmetric GARCH model (*vret*) and the unexpected realized return variance at time t (*uvret*), along with analogous variables related to the variance of volume (*vvol* and *uvvol*). Specialist revenues are measured relative to the mean of the relevant tick-size regime, and conditional variances are measured as changes from their average values during the interval $[t-10, t-6]$. Newey-West standard errors with 10 lags are in parentheses; significance at the 5% or 1% level is denoted by one or two asterisks, respectively.

	Panel A: daily observations				Panel B: weekly observations		
	GTR	ITR	RTR		GTR	ITR	RTR
Intercept	-0.625 **	-0.031	-0.594 **	*Intercept*	-3.960 **	-0.772	-3.187 **
	(0.197)	(0.104)	(0.170)		(1.175)	(0.757)	(1.103)
vret	0.551 **	0.030	0.521 **	*vret*	0.373 **	0.063	0.309 **
	(0.117)	(0.083)	(0.091)		(0.082)	(0.062)	(0.091)
uvret	-0.255 *	-0.373 **	0.118 **	*uvret*	0.002	-0.219 **	0.221 **
	(0.111)	(0.111)	(0.039)		(0.104)	(0.064)	(0.080)
ret	-0.907	-0.462	-0.445	*ret*	74.642 *	8.534	66.108 *
	(0.856)	(0.872)	(0.781)		(32.173)	(15.239)	(30.606)
vvol	0.541	1.425 *	-0.884	*vvol*	1.207	-0.483	1.690
	(0.832)	(0.633)	(0.539)		(1.978)	(1.381)	(2.449)
uvvol	-0.072	0.009	-0.081	*uvvol*	-0.047	0.150	-0.196
	(0.061)	(0.037)	(0.046)		(0.141)	(0.079)	(0.132)
vol	0.554	-0.014	0.567 *	*vol*	4.709 **	-1.974	6.683 **
	(0.303)	(0.229)	(0.237)		(1.570)	(1.484)	(1.989)
R^2	3.1%	8.8%	2.9%	R^2	3.2%	12.9%	7.7%

Table 7. Determinants of aggregate specialist revenue volatility. Time-series regressions 1994-2004. The dependent variable is the standard deviation of daily aggregate specialist revenues during week t, either aggregate gross trading revenues gtr ($millions) or one of two components: inventory-related revenues itr or round-trip revenues rtr. Explanatory variables are measured as of week $t-1$ and include the 5-week log value-weighted market return in percent, the 5-week log change in aggregate trading volumes, the time $t-1$ forecast of the time t return variance from an asymmetric GARCH model ($vret$) and the unexpected realized return variance at time t ($uvret$), along with analogous variables related to the variance of volume ($vvol$ and $uvvol$). Specialist revenues are measured relative to the mean of the relevant tick-size regime, and conditional variances are measured as changes from their average values during the interval $[t-10, t-6]$. Newey-West standard errors with 10 lags are in parentheses; significance at the 5% or 1% level is denoted by one or two asterisks, respectively.

	GTR Std Dev	ITR Std Dev	RTR Std Dev
Intercept	1.771 **	1.397 **	1.048
	(0.633)	(0.336)	(0.540)
vret	0.087 **	0.079 **	0.049 **
	(0.027)	(0.025)	(0.018)
uvret	0.074 **	0.055 **	0.039 **
	(0.019)	(0.021)	(0.010)
ret	8.853	12.740	-2.896
	(13.620)	(10.192)	(9.341)
vvol	1.221	0.589	0.761
	(0.674)	(0.702)	(0.405)
uvvol	-0.037	-0.056 *	0.016
	(0.032)	(0.027)	(0.019)
vol	0.730	0.407	0.421
	(0.533)	(0.462)	(0.307)
R^2	4.7%	13.4%	1.5%

Table 8. Cross-sectional determinants of specialist revenues. Fama-MacBeth regressions 1994-2004. The dependent variable is the sum or the standard deviation of daily specialist revenues in stock *i* during month *t*. Revenues are either gross trading revenues *gtr* ($millions) or one of two components: inventory-related revenues *itr* or round-trip revenues *rtr*. Explanatory variables are measured during month t – 1 and include the time-series average log market cap (*size*), the average daily turnover (*turn*), the inverse of the month-end share price (*invprc*), the monthly log stock return (*rets*) in percent, the average of daily log changes in dollar volume during the month (*vol*), the end-of-month *t*–1 forecast of the individual stock return variance on the first day of month *t* using an asymmetric GARCH model (*vrets*), along with an analogous variable for the variance of volume changes (*vvols*) using a symmetric GARCH model. Conditional variances are measured as changes from their average values during the interval [*t*–10, *t*–6]. T-statistics assume independence across months.

	GTR		ITR		RTR	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Dependent variable: specialist revenue						
Intercept	0.002090	0.43	-0.005540	-4.72	0.007630	1.87
size	0.043500	9.84	-0.010880	-9.69	0.054380	12.49
turnover	0.001490	4.30	-0.001900	-7.86	0.003390	10.91
invprc	0.083770	12.05	-0.009440	-3.84	0.093210	13.57
rets	-0.000081	-1.55	-0.000090	-2.13	0.000009	0.14
vols	-0.000022	-0.30	0.000056	1.29	-0.000079	-1.04
vrets	0.000327	3.85	-0.000076	-3.52	0.000403	5.10
vvols	0.027420	6.45	-0.005340	-6.21	0.032760	8.12
Dependent variable: specialist revenue / specialist dollar volume						
Intercept	0.002270	1.85	-0.000348	-0.29	0.002620	10.33
size	-0.000362	-0.91	0.000292	0.73	-0.000654	-17.20
turnover	0.000217	1.77	0.000287	2.37	-0.000070	-6.75
invprc	0.034570	1.70	0.027930	1.37	0.006640	9.88
rets	-0.000003	-0.06	0.000008	0.17	-0.000011	-2.67
vols	0.000082	1.39	0.000090	1.53	-0.000009	-1.21
vrets	-0.000407	-1.87	-0.000445	-2.03	0.000038	7.90
vvols	-0.001160	-1.08	-0.000998	-0.93	-0.000167	-1.45
Dependent variable: standard deviation of specialist revenue						
Intercept	0.004180	4.68	0.003440	8.49	0.001760	2.61
size	0.006970	3.85	0.004100	13.68	0.005510	3.16
turnover	0.000863	4.85	0.000610	13.67	0.000566	3.27
invprc	0.010160	4.63	0.005920	9.64	0.008670	4.17
rets	0.000027	1.43	0.000012	1.35	0.000026	1.75
vols	0.000033	2.08	0.000021	2.41	0.000015	1.12
vrets	0.000064	2.59	0.000032	6.61	0.000047	1.97
vvols	0.003620	5.85	0.002300	10.00	0.002620	4.41
Dependent variable: standard deviation of (specialist revenue / specialist dollar volume)						
Intercept	-0.060020	-3.70	-0.063410	-4.34	0.007250	2.01
size	-0.020170	-3.65	-0.019630	-3.72	-0.001530	-2.18
turnover	-0.002710	-1.92	-0.002690	-1.92	-0.000100	-1.71
invprc	1.825300	11.32	1.824800	11.32	0.008550	6.87
rets	-0.001510	-1.82	-0.001500	-1.82	-0.000024	-2.90
vols	-0.000009	-0.01	-0.000020	-0.03	0.000008	0.81
vrets	-0.002560	-1.94	-0.002560	-1.95	0.000048	8.42
vvols	0.087620	7.87	0.088460	8.09	-0.001070	-1.65

Figure 1. NYSE value-weighted effective spreads, 1994-2004.
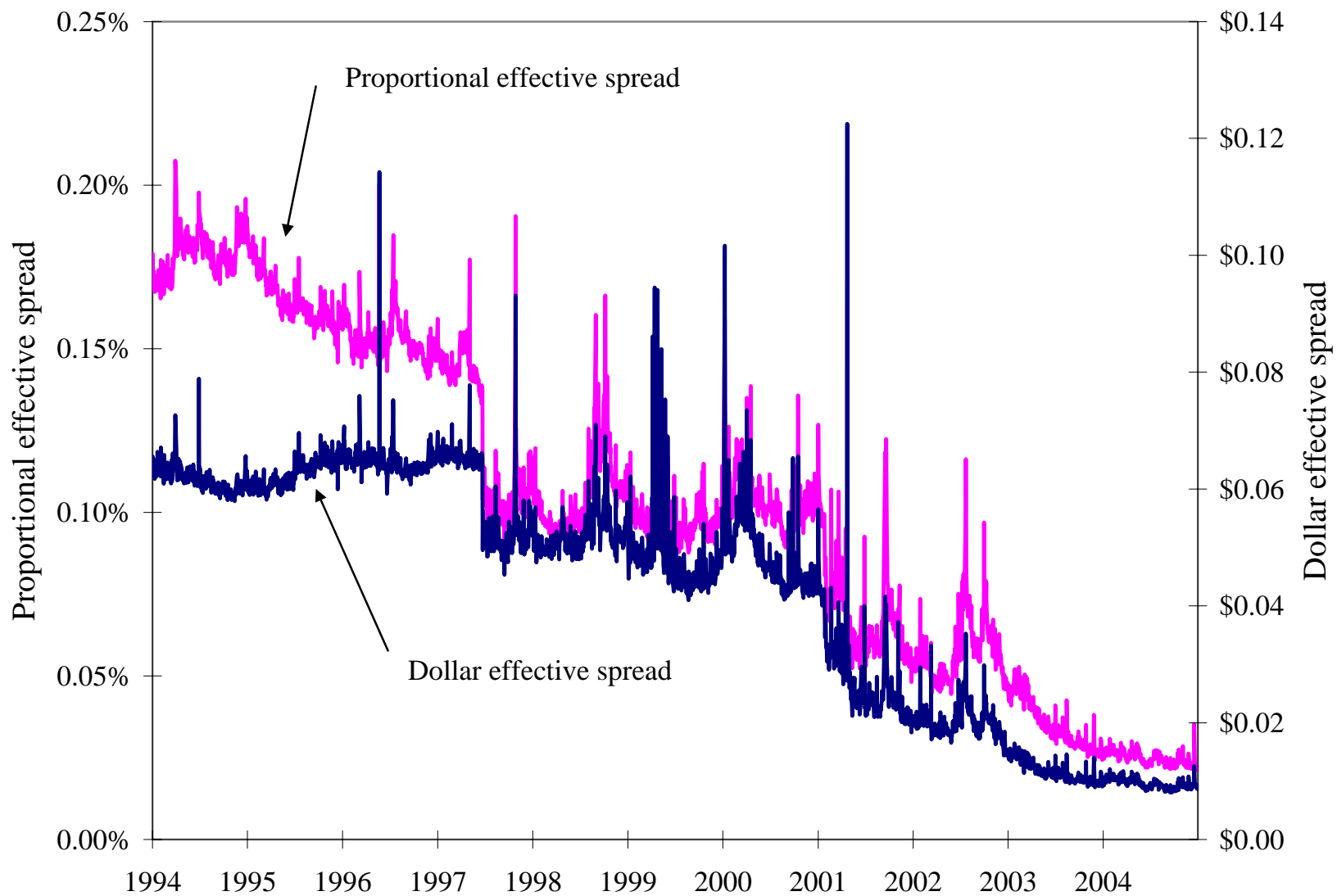
Figure 2. Impulse response functions. Responses out to 25 days to orthogonalized shocks, with error bars reflecting two standard errors. The VAR has 5 daily lags and variables in the following order: specialist overnight inventory-related revenues (*itr*), specialist intraday round-trip revenues (*rtr*), the absolute market return (*absret*), the log value-weighted market return (*ret*), and the value-weighted effective spread, measured in cents (*es*) or in basis points (*espr*). Effective spreads are detrended with a linear time trend within each tick-size regime, and specialist revenues are detrended by subtracting the mean of the relevant tick-size regime.