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Liquidity provision and stock return predictability

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ABSTRACT

This paper examines the trading behavior of two groups of liquidity providers (specialists and competing market makers) using a six-year panel of NYSE data. Trades of each group are negatively correlated with contemporaneous price changes. To test for return predictability, we sort stocks into quintiles based on each group's past trades and then form long-short portfolios. Stocks most heavily bought have significantly higher returns than stocks most heavily sold over the two weeks following a sort. Cross-sectional analysis shows smaller, more volatile, less actively traded, and less liquid stocks more often appear in the extreme quintiles. Time series analysis shows the long-short portfolio returns are positively correlated with a market-wide measure of liquidity. A double sort using past trades of specialists and competing market makers produces a long-short portfolio that earns 88 basis points per week (act as complements). Finally, we identify a "chain" of liquidity provision. Designated market makers (NYSE specialists) initially trade against order flows and prices changes. Specialists later mean revert their inventories by trading with competing market makers who appear to spread trades over a number of days. Alternatively, specialists may trade with competing market makers who arrive to market with delay.

1. Introduction

Stock returns can have a temporary and predictable short-run component in order to compensate liquidity providers for trading with less patient investors. What is the magnitude of this predictable component? What is its duration? Which types of stocks are most heavily traded by liquidity providers? This paper addresses these questions by employing six years of daily and weekly trading data from the New York Stock Exchange (NYSE). Our data contain records for two types of market makers: designated NYSE market makers (called "specialists") and competing market makers (sometime referred to as "CMMs" in this paper). Our data allow us to examine the specialists' inventory positions and the net trades of competing market makers.[1]

Studying two groups of investors who are linked to liquidity provision allows us to address a rich set of questions: Do the trades of different liquidity providers forecast stock returns in similar or different manners? How long do the designated market makers hold their positions before reverting inventories back to target levels? Do liquidity providers always trade together? Or, is there a "chain of liquidity provision" as initial positions are later transferred between members of these groups?

This paper provides an in-depth study of liquidity provider trading at daily and weekly frequencies.[2] As mentioned above, liquidity providers profit from trading with less patient investors. Such trading requires a liquidity provider to hold a suboptimal portfolio—suboptimal at efficient prices, but not at the transaction prices—until the position can be unwound. The liquidity provider profits from buying a stock below its efficient price and later selling as the price mean-reverts upward. Alternatively, the liquidity provider can sell (short) above the efficient price and later buy shares (to cover the short) as the price mean-reverts downward. Trading profits compensate a liquidity provider for risk, effort, and costs of capital.

From the financial econometrician's perspective, the act of providing liquidity (being compensated for providing a service) is

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[1] Rather than repeatedly refer to the differences in between position levels and changes in positions, we will often say stocks heavily bought or sold by liquidity providers. For competing market makers we exactly measure stocks bought and sold. Unless otherwise noted, for specialists we mean those stocks with the largest (most positive) inventories and smallest (most negative) inventories, respectively.

[2] Campbell et al. (1993), Jegadeesh and Sheridan (1995), Llorente et al. (2002), Pastor and Stambaugh (2003) and Avramov et al. (2006) provide indirect evidence of liquidity providers inducing negative autocorrelation in price changes. Hendershott and Seasholes (2007) provide direct evidence using trading data by liquidity providers.

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linked to predictability in price changes: when prices fall due to demands of sellers, prices will subsequently rise. Similarly, when prices rise due demands of buyers, prices will subsequently fall.[3] This predictability forms a bound around efficient prices and represents an empirical measure of the compensation required by liquidity providers for their services. The bound can also be thought of as a limit to arbitrage—the limit is due to risk-bearing capacity and liquidity provision.

Jagadeesh (1990) and Lehmann (1990) first observed short-horizon return reversals.[4] These reversals have been attributed to both investor overreaction and liquidity provider inventory effects—see Subrahmanyam (2005) for a discussion of this point. If there is no trading, there is no channel for inventory effects. In a market with trading, overreaction and inventory effects can work in concert. If investors trade heavily in one direction and the market for liquidity provision is less than perfectly competitive, then prices can overshoot fundamental values and subsequently reverse. We take no position on whether the source of shocks that our liquidity providers accommodate is rational or not. Instead, we show that the trading of liquidity providers is linked to subsequent price changes. Thus, we establish that liquidity providers and inventory effects play a significant role in short-run price reversion.

For both types of liquidity providers studied in this paper (specialists and competing market makers) we find their trades are negatively correlated with contemporaneous returns. The finding is consistent with liquidity providers temporarily accommodating buying and selling pressure. We sort stocks into quintiles based on each group's trading. Quintile 1 represents stocks most heavily bought and Quintile 5 represents stocks most heavily sold. We then form value-weighted, long-short portfolios using stocks in quintiles one and five (there are two different long-short portfolios based on sorting the trading of both liquidity providers). At a one-day horizon, the long-short portfolios have returns of 20 basis points and 13 basis points when sorting by the trades of specialists and competing market makers respectively.[5] To eliminate bid-ask bounce, all returns are calculated using the midpoint of closing bid-ask quotes. The cumulative weekly returns of the long-short portfolios are 41 basis points and 36 basis points and are statistically significant. The cumulative two week returns are 52 basis points and 40 basis points for specialists and competing market makers. After two weeks, the incremental returns of the long-short portfolios are no longer statistically different from zero consistent with prices having mean-reverted back to near-efficient levels.

The second part of our analysis investigates the characteristics of stocks most likely to be in the liquidity providers' highest or lowest trading quintiles. The more frequently a stock appears in Quintile 1 or Quintile 5, the more often the stock contributes to the long-short portfolio returns discussed above. We calculate the frequency with which each stock appears in the two extreme portfolios and then rank stocks by this frequency. In general, smaller, more volatile, less actively traded, and less liquid stocks appear more often in the extreme portfolios. Consistent with results in Amihud and Mendelson (1986), we find that stocks' average daily returns increase with the frequency they appear in the extreme portfolios. In other words, less liquid stocks appear to have higher returns.

Time series regressions show the returns of the long-short portfolios are related to a time series measure of effective bid-ask spreads in the market. This finding complements the cross-sectional evidence that less liquidity stocks are more often in an extreme portfolio. Taken together, the sort results, cross-sectional analysis, and time series regressions provide strong evidence that short-run return predictability is related to liquidity provision.

We employ Fama–MacBeth style regressions to show trades from one group do not drive out the predictability of trades from other groups. Trades also predict future returns above and beyond the predictability contained in only past returns. We also sort stocks into market capitalization terciles before repeating the regressions. Our results show that trades by competing market makers have the best ability to predict the returns of small stocks after controlling for specialists' inventories and past returns. Specialist inventories have the best ability to predict the returns of large stocks. The size/predictability results suggest the two groups of traders do not normally provide liquidity in the same stocks at the same time. We hypothesize that observing two groups contemporaneously providing liquidity for the same stock indicates a time of exceptionally high liquidity demand. To test this hypothesis, we double-sort stocks based on the trades of specialists and competing market makers and form a long-short portfolio. The return of the long-short portfolio is 88 basis points (on average) over the week following the double sort.

Our data allow us to better understand the inventory control behavior specialists and competing market makers. Both types of liquidity providers lean against the wind—they trade in the opposite direct as contemporaneous returns—a characteristic of both contrarian investing and liquidity provision. Both contrarian investing and liquidity provision involve buying temporarily underpriced securities and selling temporarily overpriced securities. Models of market making, however, predict that liquidity providers hold their positions for brief periods of time. Brief holding periods help manage inventory and control risk. Thus, trades of liquidity providers' should be negatively autocorrelated as in Madhavan and Smidt (1993).

We find evidence of inventory control behavior for the NYSE specialists only. They buy stocks with falling prices (sell stocks with rising prices) and revert their positions over the next few days. The half-life of the average specialist position is about 1.8 days which is far shorter than the 7.3 days reported by Madhavan and Smidt (1993) using data from fifteen years earlier. Furthermore, the negative autocorrelation is stronger (mean-reversion is faster) the larger the specialist's inventory position. We do not find evidence of competing market makers managing their inventory over short horizons as the autocorrelations of their net trades are positive for at least 10 daily lags. The positive autocorrelations may result from competing market makers having longer holding periods than specialists. Or, the positive autocorrelations may result from data that are aggregated across many different types of competing market makers. If some competing market makers provide liquidity over short horizons and others continue trading in the direction of original price movements, then detecting mean reversion in aggregate trading data becomes difficult.

It is possible the autocorrelated CMM trades result from limitations of our data and point to avenues for future research. For example, we do not currently have access to the competing market makers' portfolios (as we do for the NYSE specialists.) It is possible that the CMMs trade on the NYSE to hedge positions built up from trading on other venues. Hedging their positions may entail trading over a number of days, thus leading to positively autocorrelated

[3] Reversals can occur at intraday horizons due to market makers buying at the bid and selling at the ask. For examples, see Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1981), and Roll (1984). Over longer horizons, liquidity providers who take on positions have assumed risk which can lead to reversals—see Grossman and Miller (1988). These longer-term, inventory-induced reversals are empirically similar to, but on a larger and market-wide scale, than reversals following block trades—see Kraus and Stoll (1972).

[4] Conrad et al. (1994), Ball et al. (1995), Cooper (1999), Avramov et al. (2006), and others also study short-run reversal strategies and their profitability.

[5] The price reversals are also consistent with inventory models where a liquidity provider offers attractive prices to induce order flow on one side of the market to reduce his inventory position. For example, if other investors have been buying from the specialist, prices have been rising, and the specialist has built up a short position. The specialist then raises his quotes to the point where investors begin to sell and this selling leads to prices subsequently falling.

trades. Menkveld (2013) provides some evidence of this in his analysis of a high-frequency trader trading on both Euronext and Chi-X. Alternatively, it is possible that the CMMs are quite heterogeneous with regards to their response times. Some CMMs may trade quickly when prices are moving. Other CMMs might arrive to the market with a delay of one or more days. This second alternative would also lead financial econometricians measuring positively autocorrelated CMM trades.

We end the paper by studying with whom specialists trade as they unwind their positions. Specialist inventory positions are positively correlated with future trading by competing market makers. This lead-lag relationship is stronger when the specialists' inventory positions are large. Our findings are consistent with a model of risk sharing among liquidity providers in which one group of liquidity providers first takes on a position and then later passes it along to another group of liquidity providers.[6]

This paper builds on the historical studies of NYSE market makers, e.g., Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993), as well more recent studies. We extend and broaden the results in the most closely related paper, Hendershott and Seasholes (2007). This earlier short paper sorts stocks by conditioning on specialists' one-day inventories and follows returns for the next twelve days.[7] We also sorts stocks on inventories using conditioning periods of one day, one week, and two weeks. Additionally, we split our sample by stock size and analyze the characteristics of stocks based on how often they sort into an extreme portfolio. More importantly, we analyze the time series of long-short portfolio returns that are based on sorting specialists' inventories. We link the long-short portfolio returns to both Fama–French factors and a market-wide measure of illiquidity.

This paper differs from prior papers by analyzing specialist inventories in conjunction with trades of competing market makers and past stock returns. We show the specialists' inventories have the power to forecast future returns even after controlling for these other data series. We show how specialist inventories and trades of competing market makers can be used to identify times of extreme liquidity demands. Finally, we show evidence of inter-temporal risk sharing (trading) between specialists and the competing market makers. Our novel contributions are in four areas: (i) cross sectional properties of sorted stocks; (ii) time series properties of long-short portfolios based on sorted stocks; (iii) the ability of liquidity providers' trades to predict reversals in excess of any predictability contained in past returns; and (iv) the trades of competing market makers.

2. Data

This paper studies daily/weekly trading and returns of common stocks on the New York Stock Exchange (NYSE). An internal NYSE data file called the Specialist Summary File (SPETS) provides specialists' closing inventories for each stock on each day. A second internal file called the Consolidated Equity Audit Trail Data (CAUD) contains details of all executed orders on the NYSE including both electronic and manual orders. A data field identifies trades of competing market makers. Kaniel et al. (2008) provide a discussion of the CAUD data. We calculate buys and sells in dollars, for each stock on a daily basis.

Data from the Center for Research in Security Prices (CRSP) are used to identify firms (permno), trading volume, market capitalization, stock splits/distributions, and closing prices. The Trades and Quote database (TAQ) and master file provide the CUSIP number that corresponds to the symbol in TAQ on each date and is used to match with the NCUSIP number in the CRSP data. We consider only common stocks (SHRCLS = 10 or 11 in CRSP). The matching procedure provides a sample of 2,156 permnos (stocks). The full sample starts in January-1999 and ends December-2004. We use data in early 1999 to calculate normalized variables (see below) so the final sample starts in March-1999 and covers 1464 trading days. There are 1880 permnos with at least 250 days of data and 915 permnos with at least 1461 days of data. In total, there are more than 2.1 million stock-day observations.

To remove bid-ask bounce, close-to-close returns are calculated using bid-ask quote midpoints. The TAQ database is used to identify the closing quotes (MODE = 3 in TAQ). On days when the closing quotes are not in TAQ and on days with distributions, we use the CRSP prices/returns. The paper's results are not sensitive to whether or not we discard observations on such days. We eliminate firms with share prices over $500. The upper-price criterion eliminates Berkshire Hathaway's stock which has quotes and closing prices that differ by a factor of ten during part of the early sample period.

Table 1, Panel A shows the average fraction of daily trading volume that can be attributed to both of our liquidity providers. For both types of traders, and on each day, we sum total buys and sells in dollars and divide by twice the day's total volume (also in dollars). We report the time-series average of this fraction. Specialists account for 11.85% of total trading volume. Competing market makers account for 2.10%.

Table 1, Panel B provides cross-sectional statistics on daily specialist inventories, the net trades of competing market makers, and returns at the individual stock level. Median inventories are $33,042 per stock which corresponds to about 1% of average daily trading volume. The mean per-stock inventory is $129,602. The 1st and 99th percentiles show that specialists occasionally have closing positions more than a million dollars long or short. The positive mean inventory and large extreme long positions indicate that specialists may face an asymmetric costs structure. When specialists

Table 1
Descriptive statistics.

	NYSE specialists		Competing market makers		
Panel A: Average fractions of daily trading volume					
% of Volume	11.85%		2.10%		
	Raw variables			Normalized variables	
	$INV(\$)_{i,t}$	$CMM(\$)_{i,t}$	$r_{i,t}$	$INV_{i,t}$	$CMM_{i,t}$
Panel B: Daily cross-sectional measures					
Average	129,602	−77,914	0.07	−0.02	−0.2
Stdev	962,480	2,009,720	2.86	1.45	101.1
1st	−1,438,662	−4,903,273	−7.35	−3.69	−240.8
5th	−424,870	−1,002,384	−3.68	−1.94	−73.7
10th	−208,270	−411,521	−2.54	−1.35	−38.8
25th	−39,387	−83,002	−1.16	−0.64	−11.9
50th	33,042	−4,412	−0.01	−0.06	0.9
75th	159,653	25,730	1.19	0.56	13.9
90th	462,487	189,478	2.70	1.34	36.8
95th	881,765	502,644	3.99	1.98	66.5
99th	2,910,374	2,836,927	7.94	3.77	204.9

This table shows overview statistics for our liquidity provider trading data. Panel A shows the fraction of daily trading volume by NYSE specialists and competing market makers. Panel B shows times series averages of cross-sectional statistics. Included are daily dollar measures ("Raw Variables") and normalized measures for both groups of liquidity providers. The table also shows cross-sectional statistics of stock returns ($r_{i,t}$). Returns are measured using the mid-point of the bid-ask spread. $INV(\$)_{i,t}$ and $INV_{i,t}$, are the dollar inventories and normalized inventories of the NYSE specialists. Inventories are measured at the end of each day. $CMM(\$)_{i,t}$ and $CMM_{i,t}$ are the dollar and normalized net trades of competing market makers. The sample period starts March-1999 and ends December-2004.

[6] Hansch et al. (1998) and Reiss and Werner (1998) find evidence of risk sharing amongst market makers on the London Stock Exchange.

[7] Hendershott and Menkveld (2013) use similar NYSE specialist data to model price pressure: deviations from fundamental values due to risk-averse intermediaries supplying liquidity to asynchronously arriving investors. They use their structural model to estimate a social cost due to price pressure. Hendershott et al. (2013) examine specialist trading and inventories in conjunction with individual investors' trading. Neither of these papers examine competing market makers.

are short they need to be a buyer to return their inventory to its desired level, requiring other traders to be sellers. If some traders face short-sale constraints, the specialist can anticipate that unwinding large short positions is more difficult than unwinding large long positions. A related short-sale constraint explanation is that the NYSE up-tick rule effectively forces short sellers to provide liquidity via limit orders.

While we measure inventory levels for the NYSE specialist, our data only allow us to measure changes in holding levels, or net trades, for the CMMs. The average net trades of competing market makers (on a per-stock basis) are −$77,914. This negative value indicates that, in aggregate, either the CMMs have been reducing positions during the sample period or the CMMs use the NYSE to "lay off" positions built up from trading on other venues. Although competing market makers represent about two percent of total trading, the group experiences large variances in their net trading. At the 1st and 99th percentiles, the net trades of competing market makers are −$4,903,273 and $2,836,927.

2.1. Normalized variables

To aid cross-sectional comparisons we create normalized trading measures for each of the three liquidity providers. For NYSE specialist inventories, we follow Hendershott and Seasholes (2007) and subtract a moving average of stock *i*'s past dollar inventory levels from day *t*'s dollar inventory and divide by the standard deviation of past dollar inventory levels. The moving average and standard deviation consider lagged inventories from a three month period using trading days from $t-70$ to $t-11$:

$$\text{Normalized}: \ INV_{i,t} \equiv \frac{Inventory(\$)_{i,t} - MA\{Inventory(\$)_{i,[t=-70,t=-11]}\}}{Stdev\{Inventory(\$)_{i,[t=-70,t=-11]}\}}$$

For the net trades of competing market makers, we follow the procedure Kaniel et al. (2008) use for individuals in CAUD and to identify periods of intense buying or selling. We divide net dollar volume by the stock's average dollar volume over the previous year. We then subtract a moving average of this measure. For competing market makers, the expression is:

$$X_{i,t} = \frac{\text{Buy Volume}(\$)_{i,t}^{CMM} - \text{Sell Volume}(\$)_{i,t}^{CMM}}{\text{Average Volume}(\$)\text{Over Previous Year}_{i,t}}$$

$$\text{Normalized}: \ CMM_{i,t} \equiv X_{i,t} - MA\{X_{i,[t-70,t-11]}\}$$

Table 1, Panel B also provides daily cross-sectional statistics for the two normalized variables used in this paper. Normalized inventories ($INV_{i,t}$) are −3.69 and +3.77 at the 1st and 99th percentiles. The average 1st and 99th percentiles values of the net trading variables ($CMM_{i,t}$) are much larger. Normalized net trades of competing market makers have average values of −240.8 and +204.9 at the 1st and 99th percentiles. Unless otherwise noted, the results in this paper use the normalized variables.

2.2. Leaning against the wind

We test whether our liquidity provision variables are negatively correlated with contemporaneous returns. For each of the 915 stocks in our sample with at least 1461 days of data, we measure the contemporaneous correlation of liquidity provision variables and returns. We report a cross-sectional average of these time-series correlations.[8]

[8] Results are qualitatively similar if we consider the 1880 permnos (stocks) with at least 250 days of data and available from authors upon request.

Table 2
Contemporaneous correlations.

	Raw Variables			Normalized
	$INV(\$)_{i,t}$	$CMM(\$)_{i,t}$	$r_{i,t}$	$INV_{i,t}$
$CMM(\$)_{i,t}$	0.066			
	(0.24)			
$r_{i,t}$	-0.306	-0.144		
	(0.00)	*(0.17)*		
$INV_{i,t}$	0.783	0.059	-0.320	
	(0.00)	*(0.23)*	*(0.00)*	
$CMM_{i,t}$	0.070	0.849	-0.152	0.074
	(0.20)	*(0.00)*	*(0.16)*	*(0.19)*

This table shows the contemporaneous correlations of daily liquidity provider trading variables and stock returns. We consider NYSE specialist inventories (*INV*) and competing market makers (*CMM*). Correlations are first calculated for each stock in our sample. The table reports cross-sectional averages. Below each correlation is the fraction of stocks with a correlation of opposite sign from that of the average. Returns are measured using the mid-point of the bid-ask spread. Inventories are measured at the end of each day. We consider dollar values ($) and normalized variables as described in the text. The sample period starts March-1999 and ends December-2004.

Table 2 shows that a NYSE specialist's inventory levels (in dollars) and returns have a −0.306 correlation. To gauge significance, we record the fraction of stocks with a correlation that is opposite in sign to the average. In the case of inventories and returns, less than 1% of stocks have a positive correlation. The net trades of competing market makers have a −0.144 correlation with returns. However, 17% of the respective correlations using net trades are positive. The 17% provides evidence consistent with the two previously-mentioned phenomena (CMMs either lay-off positions built up on other venues or CMMs are heterogeneous in the response time to price movements.) Correlations using our normalized variables give qualitatively similar results.

Table 2 also highlights some positive correlation among the trades of liquidity providers. When NYSE specialists are long stock, competing market makers tend to be buying. The correlation of $INV(\$)_{i,t}$ and $CMM(\$)_{i,t}$ is 0.066. Note that the positive correlation of 0.066 indicates the two groups do buy together but the relationship is not too strong. Similar results hold when using normalized variables.

3. Liquidity provision and stock return predictability

3.1. Single-sort procedure

We sort stocks into quintiles based on the daily trades of liquidity providers in order to quantify the economic magnitude of return predictability. For completeness, we consider sorting stocks based on current values of a liquidity provision variable (day $t=0$), the past week's values $[t-4, t=0]$, and the past two week's values $[t-9, t=0]$. We form value-weighted long-short portfolios using stocks in Quintile 1 and Quintile 5. The portfolios buy stocks that liquidity providers have been buying and sell stocks that liquidity providers have been selling. Throughout the paper, we focus on the returns of these long-short portfolios which are measured on days $t+1, t+2, \ldots, t+5$, and $t+10$. We also measure cumulative return over one week $[t+1, t+5]$ and over two weeks $[t+1, t+10]$.

Table 3, Panel A sorts using the normalized measure of NYSE specialist inventories ($INV_{i,t}$). Sorting by only day *t*'s inventories predicts returns of 17 bp after one day, 33 bp over one week (cumulative), and 42 bp over two weeks (cumulative). Sorting using the average inventory level over the past week $[t-4, t=0]$ predicts returns of 20 bp after one day, 41 bp over one week (cumulative), and 52 bp over two weeks (cumulative). *T*-statistics are shown in parentheses below the returns of the long-short portfolios and are based on Newey–West standard errors. Note that the incremental return on day $t + 10$ only is no longer statistically significant and T-statistics range from 0.56 to 1.29.

Table 3, Panel B sorts using the normalized measure of net trades by competing market makers ($CMM_{i,t}$). Based on sorting over $[t-4, t=0]$, predictable returns are 36 bp and 40 bp after one and two weeks respectively.

To compare our results to related work on return reversals such as Jagadeesh (1990) and Lehmann (1990), and others, we end Table 3 with return sorts. Long-short portfolios based on returns sorts are long stocks in the low (negative) return quintile and short stocks in the high (positive) return quintile. Sorting using returns over the past week $[t-4, t=0]$ predicts returns of 15 bp after one day, 57 bp over one week (cumulative), and 77 bp over two weeks (cumulative). The magnitude of the return-sort predictability is smaller than those shown in Lehmann (1990) because our portfolios use value-weighted returns whereas the earlier paper employs portfolios weights based on the absolute value of returns.

To gain insight into the return predictability of large and small stocks, we sort our sample of stocks into market capitalization terciles each day. To avoid confounding returns and size, we use market capitalization lagged by eleven days. For each size tercile, we perform a similar sorting procedure as the one shown in Table 3 except we limit ourselves to sorting by the past week's variables, $[t-4, t=0]$, only. Fig. 1 graphs the returns, net of the market, for the long-short portfolio over the two-week period following the sort (i.e., $[t+1, t+10]$).

Fig. 1, Panel A shows results based on inventory sorts. We graph only the large and small terciles (by market capitalization). For large stocks with high past inventories over the period $[t-4, t=0]$, prices rise for four days before leveling off. For large stocks with low (negative) inventories, prices fall over the next two weeks. Small stocks may have predictability beyond two weeks—the high portfolio rises and the low (negative) portfolio falls throughout the two week holding period shown in the figure.

Fig. 1, Panel B shows predictability using the net trades of competing market makers. Most of the return predictability follows periods of buying (not selling) by competing market makers. This fact may be related to the CMMs selling, on average, throughout our sample period. If some competing market makers are randomly selling from time to time, the sorting procedure may not well identify the stocks where aggregate selling by this group is associated with liquidity provision versus selling for other reasons. Alternatively, the CMMs may buy in the NYSE to cover short positions built up in other markets. Large stocks revert by approximately 40 bp over two weeks—the amount of large-stock reversion can be roughly seen as the distance between the "Large-Hi" and "Large-Lo" graph lines.

Fig. 1, Panel C shows predictability using stock returns. Large stocks have noticeably more predictability than small stocks. Large stocks with low (negative) returns over the period $[t-4, t=0]$, tend to go up 32 bp (basis points) over the following week. Large stocks with high (positive) returns over the period $[t-4, t=0]$, tend to go down 28 bp (basis points) over the following week. The net difference for the large stocks is 60 bp over the week. This is slightly more than the 57 bp shown in Table 3, Panel C for all stocks. The difference is due to small stocks having lower predictability over the one week horizon.

The single-sort results in Table 3 and Fig. 1 provoke a number of questions which we address in the following sub-sections: (3.2) What types of stocks tend to sort into the extreme portfolios (Quintile 1 and Quintile 5)? Do the three sorting strategies shown in Table 3 tend to put similar or different type of stocks in the extreme portfolios? (3.3) What are the time series properties of the returns on the long-short portfolios based on liquidity provider trading? Are the returns correlated with Fama–French factors or measures of liquidity? (3.4) Do the returns of the three sorting procedures represent a single predictability phenomenon or, is there an incremental ability to forecast returns using our liquidity supplier variables? (3.5) Can trades of two liquidity providers be used to predict times of extreme illiquidity?

3.2. Characteristics of reversal stocks

To examine stock characteristics, we employ a sequence of two single-sort procedures. We start with a typical single-sort

Table 3
Single sort results.

Sorting ↓ Period	Returns of long-short portfolios over the following periods							
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+10$	$[t+1, t+5]$	$[t+1, t+10]$
Panel A: Sort by Specialists' Inventories (INV)								
$t=0$	0.17	0.09	0.07	0.04	−0.03	0.05	0.33	0.42
	(3.21)	*(3.49)*	*(1.63)*	*(1.40)*	*(−0.87)*	*(1.29)*	*(4.79)*	*(3.47)*
$[t-4, t=0]$	0.20	0.06	0.15	0.03	−0.02	0.05	0.41	0.52
	(2.79)	*(1.64)*	*(3.77)*	*(0.66)*	*(−0.54)*	*(1.09)*	*(3.84)*	*(3.05)*
$[t-9, t=0]$	0.14	0.03	0.10	0.02	0.01	−0.02	0.30	0.30
	(2.93)	*(0.89)*	*(2.81)*	*(0.43)*	*(0.36)*	*(−0.56)*	*(2.64)*	*(1.39)*
Panel B: Sort by net trades of Competing Market Makers (CMM)								
$t=0$	0.16	0.05	0.04	0.05	0.03	0.08	0.33	0.55
	(2.41)	*(1.24)*	*(0.80)*	*(1.10)*	*(0.64)*	*(1.64)*	*(4.29)*	*(3.75)*
$[t-4, t=0]$	0.13	0.07	0.07	0.07	0.03	−0.02	0.36	0.40
	(1.99)	*(1.31)*	*(1.45)*	*(1.24)*	*(0.79)*	*(−0.69)*	*(2.67)*	*(2.08)*
$[t-9, t=0]$	0.07	0.00	0.04	0.05	0.01	0.01	0.17	0.20
	(2.02)	*(0.11)*	*(0.91)*	*(0.88)*	*(0.35)*	*(0.21)*	*(1.92)*	*(1.01)*
Panel C: Sort by returns (r)								
$t=0$	0.03	0.12	0.09	−0.01	−0.03	0.11	0.21	0.51
	(0.64)	*(2.41)*	*(1.85)*	*(−0.17)*	*(−0.64)*	*(2.17)*	*(2.50)*	*(2.71)*
$[t-4, t=0]$	0.15	0.18	0.22	0.03	0.00	−0.10	0.57	0.77
	(1.93)	*(2.00)*	*(3.09)*	*(0.48)*	*(−0.04)*	*(−1.33)*	*(3.92)*	*(4.25)*
$[t-9, t=0]$	0.26	0.11	0.22	0.10	−0.09	−0.03	0.60	0.74
	(3.57)	*(2.29)*	*(3.27)*	*(1.57)*	*(−1.14)*	*(−0.33)*	*(3.91)*	*(2.36)*

This table shows results of three single sorting procedures. Sort variables include NYSE specialist inventories ($INV_{i,t}$), net trades of competing market makers ($CMM_{i,t}$), and returns ($r_{i,t}$). For each quintile, we form a portfolio of stocks and measure the value-weighted return over following ten days ($t+1, t+2, \ldots, t+10$). The tables show the returns of long-short portfolios using Quintiles 1 and 5. Cumulative long-short portfolio returns over the following week $[t+1, t+5]$ and two weeks $[t+1, t+10]$ are also shown. T-statistics are shown in parentheses and are based on Newey–West standard errors.

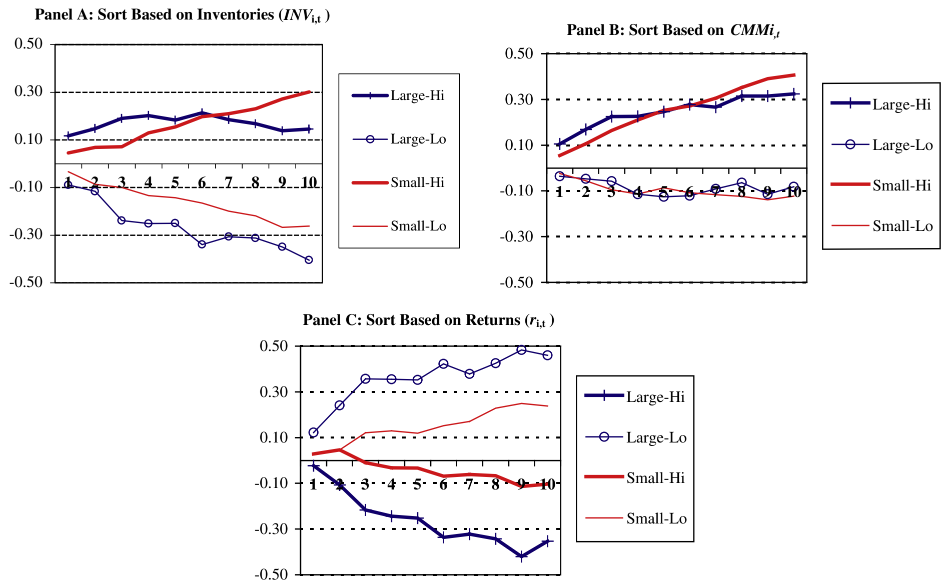

Fig. 1. Single sort results. This figure shows results of three single sorting procedure based NYSE specialist inventories (INV_i), net trades of competing market makers (CMM_i), and returns (r_i). Before sorting, stocks are divided into terciles by size (market capitalization) on day $t-11$. "Large" indicates stocks in the top size tercile and "Small" indicates stocks in the lowest size tercile. We sort stocks into quintiles based on variable values over the past five days $[t-4, t=0]$. For each quintile, we form a portfolio of stocks, value-weight returns, and show cumulative returns, net of the market, over the following week two weeks $[t+1, t+10]$.

methodology based on the past week of NYSE inventories, the net trades of competing market makers, or returns. For each of the 915 stocks with at least 1461 days of data, we calculate the fraction of weeks the stock is in an extreme sort portfolio (Quintile 1 or Quintile 5). We then rank (re-sort) stocks by this fraction from lowest (stocks that least often in an extreme portfolio) to highest (stocks that are most often in an extreme portfolio). Table 4 summarizes the results. Note that in a purely random world, each stock should spend 0.200 of the days in each quintile and 0.400 of the days in either of the two extreme quintiles.

Table 4, Panel A shows results for stocks that have first been sorted by NYSE specialist inventory over the past week $[t-4, t=0]$. Based on the frequency in an extreme portfolio, the lower 20% of stocks spends an average of 0.262 of the time in an extreme portfolio. The upper 20% of stocks spends an average of 0.513 of the time an extreme portfolio. It is the latter group of stocks that most heavily influences the returns of the long-short portfolios shown in Table 3 and Fig. 1. Inventory sorts tend to place medium sized stocks in extreme portfolios and the average market capitalization of these stocks is $7.12 billion. These stocks are slightly more volatile than average with $\sigma(r) = 2.76\%$, have lower turnover of 0.44%, larger spreads of 0.28%, higher values of the Amihud (2002) illiquidity measure of 4.83%, and slightly higher than average returns of 0.08%.

Table 4, Panel B shows results for stocks that have first been sorted by $CMM_{i,t}$ over the past week $[t-4, t=0]$. These CMM-sorts tend to put small, illiquid stocks in the extreme portfolios. The average market capitalization of stocks most likely to sort into an

Table 4
Characteristics of sorted stocks.

Fraction of days in an extreme portfolio		MktCap $ billion	Return Stdev (%)	Average turn (%)	Spreads (%)	Illiq. (%)	Average return (%)
Panel A: Sort by Specialists' Inventories (INV)							
Least Often	0.262	18.05	2.51	0.57	0.11	0.34	0.06
	0.303	11.25	2.49	0.60	0.11	0.32	0.07
	0.343	5.77	2.65	0.57	0.16	0.96	0.08
	0.403	2.18	2.81	0.58	0.21	2.13	0.09
Most Often	0.513	7.12	2.76	0.44	0.28	4.83	0.08
Panel B: Sort by net trades of Competing Market Makers (CMM)							
Least Often	0.119	12.02	2.29	0.61	0.08	0.10	0.06
	0.229	9.74	2.48	0.59	0.11	0.26	0.07
	0.326	11.73	2.62	0.60	0.13	0.59	0.08
	0.443	9.32	2.80	0.54	0.19	1.37	0.08
Most Often	0.624	1.56	3.04	0.42	0.35	6.27	0.09
Panel C: Sort by returns (r)							
Least Often	0.213	9.39	1.74	0.34	0.11	0.50	0.06
	0.295	14.72	2.09	0.44	0.12	0.88	0.06
	0.364	11.99	2.45	0.52	0.14	0.96	0.07
	0.448	4.20	2.92	0.65	0.19	2.10	0.09
Most Often	0.573	4.07	4.02	0.81	0.31	4.14	0.10

This table shows characteristics of sorted stocks. We first perform a single sort procedure. We next rank (re-sort) stocks by the fraction of days it is in an extreme sort portfolio. Stocks labeled "least often" sort least frequently into Quintiles 1 or 5. Stocks labeled "most often" sort most frequently into Quintiles 1 or 5. For each stock, we record its average market capitalization over the sample period, standard deviation of returns, average daily turnover, average effective spread, average Amihud measure of illiquidity ("Illiq."), and average daily return.

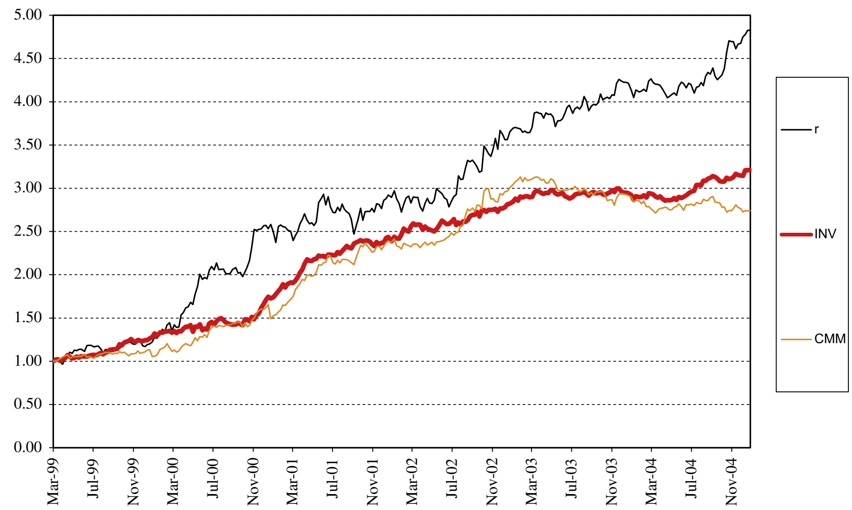

Fig. 2. Cumulative strategy returns. This table shows the cumulative returns of three long-short portfolios that result from three single sorting procedures. Sort variables include NYSE specialist inventories ($INV_{i,t}$), net trades of competing market makers ($CMM_{i,t}$), and returns ($r_{i,t}$). We sort stocks using data over the past week [$t-4$, $t=0$]. Portfolios are held for the following week [$t+1, t+5$]. The returns of a long-short portfolio is equal to the difference between the returns of extreme sort portfolios (Quintiles 1 and 5).

extreme portfolio is \$1.56 billion, the volatility of returns is 3.04%, turnover is 0.42%, spreads are 0.35%, the Amihud (2002) value of illiquidity is 6.27%, and the average return is 0.09%. The table makes it clear that sorting by $CMM_{i,t}$ puts small, illiquid stocks in extreme quintiles. These stocks are used to form the long-short portfolios shown in Table 3, Panel B.

Panel C shows that sorting by returns, $r_{i,t}$, puts medium to small-sized firms in the extreme quintiles. Due to the fact that portfolios are formed on the basis of past returns, it is not surprising that stocks in the extreme portfolios have an average return volatility of 4.02%. Interestingly, these stocks also have high turnover of 0.81%, and high average returns of 0.10%.

To summarize, sorting procedures that predict short-horizon returns based on liquidity provider trading tend to place small, illiquid stocks in extreme portfolios. The prevalence of small stocks in extreme portfolios is particularly noticeable when sorting by the net trades of competing market makers. In the latter case, stocks with an average market capitalization of only \$1.56 billion spend an average of 0.624 of the days in extreme portfolios.

3.3. Time series properties of sorted portfolios

We examine the time-series properties of the long-short portfolios shown in Table 3. We focus on portfolios formed by sorting over the past $[t-4, t=0]$ interval and holding stocks over the future $[t+1, t+5]$ interval. Fig. 2 graphs the cumulative returns based on sorting by NYSE specialist inventories, net trades of competing market makers, and past returns. As shown in Table 3, sorting by past returns gives the largest returns.

The returns of the three long-short portfolios are positively correlated. For example, the correlation of returns from the inventory long-short portfolio is 0.3697 with the returns from the CMM long-short portfolio. Also, the correlation of returns from the inventory long-short portfolio is 0.3126 with the return-sorted long-short portfolio.

We test whether the returns of the three long-short portfolios are correlated with Fama–French and momentum factors. We also test whether returns are correlated with a market-wide measure of liquidity—the effective spread.[9] Table 5 presents our results.

[9] We calculate each stock's effective spread each day by volume weighting transactions throughout the day—see Comerton-Forde et al. (2010) for a complete explanation of spread calculations. We equal-weight spreads each day to obtain a market-wide measure.

Results using the long-short portfolio returns based on NYSE specialist inventory sorts are shown in Regression #1a and #1b. In Regression #1a, notice that returns load negatively on *SMB* with a −13.26 coefficient and −2.07 *T*-statistic. Throughout the table, coefficients have been multiplied by 100. The long-short portfolio returns load positively on *UMD* with an 8.71 coefficient and a 2.20 *T*-statistic. Regression #1b adds market-wide spreads and a time trend to the regression. The coefficient on *SMB* is no longer statistically significant while the coefficient on *UMD* remains so.

The most important feature of Table 5 is the positive loading on our market-wide measure of liquidity as shown in Regression #1b. The coefficient on effective spreads is 85.34 with a 2.89 *T*-statistic. This result indicates that liquidity providers earn higher returns at times when average spreads are wider and lower return at times when average spreads are narrower. The result, however, is not driven by spreads themselves as returns in our paper use bid-ask quote midpoints.

The returns of a long-short portfolio based on *CMM* sorts are shown in Regression #2a and #2b and are not significantly correlated with any factor. Finally, the returns of a return-based long-short portfolio, in Regressions #4a and #4b, show no correlation with Fama–French factors, momentum factors, nor with spreads.

To summarize, strategies based on mimicking the trades of NYSE specialists are more profitable at times when market-wide spreads are wider. This result provides further evidence that the return predictability documented in this paper is linked to liquidity provision. Interestingly, the strategies are also more profitable at times the momentum portfolio (*UMD*) exhibits higher returns. Understanding the relation between the *UMD* returns (formed on the basis of six-month momentum sorts) and the returns of a long-short portfolio (formed on the basis of a one-week reversal sort) is a topic for future research. Sadka (2006) has initiated research along this line.

3.4. Fama–Macbeth regressions

We use Fama–Macbeth regressions to test whether NYSE inventories and/or the net trades of competing market makers predict future returns in excess of the predictability contained in past returns alone. In other words, we test whether specialists' inventories and competing market makers net trades acts as complements or substitutes when it comes to predicting reversals. The dependent regression variable is the return of stock i over the time period

Table 5
Time-series regressions from single sorts.

	Long-short portfolio based on INV sort		Long-short portfolio based on CMM sort		Long-short portfolio based on ret sort	
	Reg #1a	Reg #1b	Reg #2a	Reg #2b	Reg #3a	Reg #3b
Dependent variable: Returns from a long-short portfolio						
rm − rf	0.65	0.88	7.05	7.41	12.68	13.06
	(0.16)	*(0.23)*	*(1.08)*	*(1.12)*	*(1.56)*	*(1.58)*
SMB	−13.26.	−11.48	−14.14	−12.53	−17.14	−15.11
	(−2.07)	*(−1.79)*	*(−1.70)*	*(−1.36)*	*(−1.27)*	*(−1.10)*
HML	−7.31	−6.89	10.10	10.68	1.60	2.24
	(−1.13)	*(−1.10)*	*(1.43)*	*(1.54)*	*(0.12)*	*(0.17)*
UMD	8.71	8.66	14.25	14.05	−6.80	−6.98
	(2.20)	*(2.15)*	*(2.13)*	*(1.98)*	*(−0.80)*	*(−0.79)*
Spreads		85.34		75.22		95.64
		(2.89)		*(1.55)*		*(1.48)*
Time Trend		0.00		0.00		0.00
		(1.82)		*(0.77)*		*(0.81)*
Constant	0.43	−1.35	0.34	−1.10	0.62	−1.27
	(5.59)	*(−1.89)*	*(3.13)*	*(−0.96)*	*(4.24)*	*(−0.83)*

This table shows time series regressions based on three single sort results. The dependent variables are the returns, in percentage, of the three long-short portfolios shown in Table 3. Independent variables include the market excess return (*rm − rf*), Fama–French size factor (SMB_t), Fama–French size factor (HML_t), momentum factor (UMD_t), equal-weighted measure of effective spreads in our sample ($Spreads_t$), and a time trend variable. *T*-statistics are shown in parentheses and are based on Newey–West standard errors.

$[t+1, t+5]$. The independent variables consists of a series of indicators. We set the first indicator equal to one if stock *i* is in the highest inventory quintile measured over the $[t-4, t=0]$ interval. We set the second indicator equal to one if stock *i* is in the lowest inventory quintile over the same interval. We set the third (fourth) indicator equal to one if stock *i* is in its highest (lowest) *CMM* quintile over the time period $[t-4, t=0]$, respectively. Finally, we set the fifth (sixth) indicator equal to one if stock *i* is in its highest (lowest) *return* quintile over the time period $[t-4, t=0]$, respectively. The regressions have the advantage that many predictor variables can be tested simultaneously. The methodology avoids sorting stocks along multiple dimensions which results in sparsely populated bins.

Table 6 shows time-series averages of weekly estimated coefficients. In order to increase comparability with the sorting results, we report the difference in pairs of estimated coefficients (high minus low) for *INV* and *CMM*. For *returns*, we report the difference of low minus high.

Table 6, Regression 1 shows an inventory high minus low difference of 23 bp per week with a 5.16 *T*-statistic. This high minus low value differs from the 41 bp shown in Table 3 due to the fact that Fama–Macbeth regressions treat each stock (over the same week) as an equal observation. In other words, the earlier table reports value-weighted portfolio returns while the Fama–Macbeth regressions effectively report equal-weighted portfolio returns. Fig. 1, Panel A confirms that a value-weighted portfolio should outperform an equal-weighted portfolio. Over the $[t+1, t+5]$ horizon following an inventory sort, the figure shows that large stocks outperform small stocks.

The effect of size becomes particularly apparent when looking at the return difference (low minus high) in Table 6, Regression 3. The return difference is only 26 bp with at 3.11 *T*-statistic. Again, the Fama–Macbeth regressions are akin to equal-weighted sort methodology and Fig. 1, Panel C shows that equal-weighted return sorts do not have nearly the predictive power as value-weighted return sorts.

Table 6, Regression 4 tests for significance of indicator differences when all three sorting variables are included in the regression. The difference in the inventory high minus low indicator variables is 14 bp with a 3.20 *T*-statistic. For *CMM*s, the difference is 30 bp with a 3.82 *T*-statistic. Finally, for returns, the difference is 18 bp with a 2.14 *T*-statistic. Most importantly, Regression 4 shows that the trades of both liquidity providers help predict returns above and beyond the predictability contained in past returns.

To understand/confirm the role of stock market capitalization in return predictability, we divide our sample into size terciles and then repeat the Fama–Macbeth regressions. Inventories have an increasing ability to predict reversals as we move from small to large stocks (Table 6, Regressions 5 to Regression 7). CMMs exhibit the largest marginal ability to predict the returns of small stocks. By marginal, we mean after "controlling" for the predictability of specialist inventories and past returns. The ability of returns to predict reversals is highest for large stocks. Following a return sort, the difference between low and high indicator variables is 0.21 for

Table 6
Fama Macbeth regressions.

		Reg #1	Reg #2	Reg #3	Reg #4	Reg #5 Small	Reg #6 Medium	Reg #7 Large
Dependent variable: Return of Stock i over days [t + 1, t + 5]								
$INV_{i,t}$	*Hi − Lo*	0.23			0.14	0.11	0.18	0.23
		(5.16)			*(3.20)*	*(1.51)*	*(2.04)*	*(3.81)*
$CMM_{i,t}$	*Hi − Lo*		0.30		0.30	0.29	0.11	0.09
			(4.71)		*(3.82)*	*(4.32)*	*(1.40)*	*(0.93)*
$r_{i,t}$	*Hi − Lo*			0.26	0.18	0.21	0.14	0.36
				(3.11)	*(2.14)*	*(1.71)*	*(1.62)*	*(3.44)*
Const		0.34	0.28	0.30	0.23	0.22	0.28	0.20
		(2.40)	*(1.97)*	*(2.31)*	*(1.62)*	*(0.95)*	*(1.97)*	*(1.69)*

This table shows results of Fama–Macbeth cross-sectional regressions. Each week, the returns of stock *i* over days $[t+1, t+5]$ are regressed on a series of indicator variables. We include variables indicating whether stock *i* sorts into a "*Hi*" portfolio (Quintile 1) or a "*Lo*" portfolio (Quintile 5). Sorts are based on NYSE specialist inventories ($INV_{i,t}$), net trades of competing market makers ($CMM_{i,t}$), and returns ($r_{i,t}$). We report is the difference between the estimated values of indicator variables ("*Hi − Lo*") for *INV* and *CMM*. We report "*Lo − Hi*" for returns (*r*). The right hand side of the table repeats Regression #4 for stocks in the small, medium, and large size terciles. *T*-statistics are shown in parentheses and are based on Newey–West standard errors.

small stocks, 0.14 for medium stocks, and 0.36 with a 3.44 *T*-statistic for large stocks.

3.5. Double sorts

We test whether the trading behavior of liquidity providers can be used to identify periods of large return predictability. In particular, we are interested in whether the net trades can be used to construct a strategy with average returns greater than or equal to the 57 bp per week obtained by the single return sort (shown in Table 3, Panel C).

We independently double sort stocks into quintiles based on liquidity provision variables from days $[t-4, t=0]$. After sorting, we form value-weighted portfolios of stocks in each of the 25 bins and measure returns over the next week $[t+1, t+5]$.

Table 7, Panel A reports the results of a double sort using specialists' inventories and the net trades of competing market makers. We report the average return of all 25 bins (portfolios). Returns over the next week increase as we move from the top-left to the bottom-right of the table. We also report return differentials while keeping one sort variable constant. Using the top row as an example, a portfolio that is long *Hi-CMM & Lo-INV* stocks and short *Lo-CMM & Lo-INV* stocks earns 26 bp over the next week and this return has a 1.23 *T*-statistic. Using the first column as a second example, a portfolio that is long *Hi-INV & Lo-CMM* stocks and short *Lo-INV & Lo-CMM* stocks earns 49 bp over the next week with a 2.95 *T*-statistic.

Table 7, Panel A also reports the average return of the portfolio we expect to exhibit the largest reversals—labeled the "Extreme Reversal Portfolio". In the case of an *INV-CMM* double sort, the extreme reversal portfolio is long *Hi-INV & Hi-CMM* stocks and is short *Lo-INV & Lo-CMM* stocks. This portfolio earns 88 bp per week and has a 4.73 *T*-statistic. The standard deviation of the extreme reversal portfolio's returns is 2.79% per week which leads to an annualized Sharpe Ratio of approximately 2.28. More importantly, the extreme reversal portfolio produces average returns that are both economically and statistically greater than the long-short portfolio based on only a return sort (see the 57 bp return in Table 3, Panel C). The return difference between the extreme reversal portfolio and the single return-sort portfolio is 31 bp per week and has a 2.12 *T*-statistic.

Table 7, Panel B summarizes the results of three other double sorts with a focus on the returns of the extreme reversal portfolios. The third double sort in Panel B repeats the results shown in Panel A directly above. In the first row of Panel B, we see that a portfolio that is long *Hi-INV & Lo-Ret* stocks and short *Lo-INV* & *Hi-Ret* stocks earns 85 bp per week with a 5.08 *T*-statistic.

To conclude, our double sort results show that using the NYSE specialist inventories and the net trades of competing market makers can be used to predict returns of 88 bp per week. This magnitude of predicted returns is significantly greater than using only past returns (or any other single variable) as a conditioning variable. When both types of traders are providing liquidity, we believe liquidity demands are particularly high. During such times, the compensation for providing liquidity is also high. The high compensation can be measured by the 88 bp per week average return of the extreme reversal portfolio.

Table 7
Double sort results.

Panel A: Double Sort by Inventories ($INV_{i,t}$) and Net Trades of Competing Market Makers ($CMM_{i,t}$)
Returns Over *[t+1,t+5] Shown*

		Net Trades of CMMs						CMM Effect	
		Lo (-)	2	3	4	Hi (+)			
INV	Lo (-)	**-0.32**	0.05	0.11	0.33	-0.07		0.26	(1.23)
	2	-0.13	0.06	0.01	0.41	0.42		0.55	(2.70)
	3	0.04	-0.01	0.17	0.05	0.27		0.23	(1.38)
	4	0.08	0.02	0.06	0.22	0.33		0.25	(1.49)
	Hi (+)	0.17	0.22	0.36	0.36	**0.56**		0.39	(2.70)
	INV Effect	0.49	0.17	0.24	0.03	0.62	↘	**0.88**	*Extreme Reversal Portfolio*
		(2.95)	*(0.74)*	*(1.55)*	*(0.17)*	*(2.51)*		*(4.73)*	

Panel B: Overview of Double Sorts*

Sort #1	Sort #2	Long Portfolio	Short Portfolio	Return Over [t+1, t+5]	(T-Stat)
$INV_{i,t}$	$r_{i,t}$	Hi-INV & Lo-Ret	Lo-INV & Hi-Ret	0.85	*(5.08)*
$CMM_{i,t}$	$r_{i,t}$	Hi-CMM & Lo-Ret	Lo-CMM & Hi-Ret	0.76	*(3.66)*
$CMM_{i,t}$	$INV_{i,t}$	Hi-CMM & Hi-INV	Lo-CMM & Lo-INV	0.88	*(4.73)*

* *The details of the third double sort are shown in Panel A directly above.*

This table shows results of double sorting procedures. Sort variables include NYSE specialist inventories ($INV_{i,t}$), net trades of competing market makers ($CMM_{i,t}$), and returns ($r_{i,t}$). We sort variables using values over the past week $[t-4, t=0]$. For each of the 25 bins, we form a portfolio of stocks and measure the value-weighted return over the following week $[t+1, t+5]$. Panel A shows average returns for each of the 25 bins based on a double sort using NYSE specialist inventories (*INV*) and trades of competing market makers (*CMM*). Panel B summarizes the return of the extreme reversal portfolio over the following week $[t+1, t+5]$ from three different double sorts. *T*-statistics are shown in parentheses and are based on Newey–West standard errors.

Table 8
Cross-sectional averages of auto-correlation coefficients.

	Raw variables				Normalized variables	
	$INV(\$)_{i,t}$	$\Delta INV(\$)_{i,t}$	$CMM(\$)_{i,t}$	$r_{i,t}$	$INV_{i,t}$	$CMM_{i,t}$
AR(1)	0.542	−0.322	0.252	−0.004	0.473	0.261
	(0.00)	*(0.00)*	*(0.01)*	*(0.50)*	*(0.00)*	*(0.00)*
AR(2)	0.417	−0.069	0.164	−0.016	0.349	0.178
	(0.01)	*(0.08)*	*(0.04)*	*(0.32)*	*(0.00)*	*(0.02)*
AR(3)	0.352	−0.026	0.136	0.003	0.285	0.149
	(0.01)	*(0.28)*	*(0.04)*	*(0.48)*	*(0.00)*	*(0.02)*
AR(4)	0.308	−0.020	0.120	−0.003	0.240	0.132
	(0.02)	*(0.34)*	*(0.06)*	*(0.46)*	*(0.01)*	*(0.03)*
AR(5)	0.278	−0.012	0.109	−0.010	0.207	0.121
	(0.03)	*(0.37)*	*(0.06)*	*(0.36)*	*(0.02)*	*(0.03)*
AR(6)	0.256	−0.007	0.100	−0.011	0.183	0.110
	(0.03)	*(0.44)*	*(0.08)*	*(0.37)*	*(0.03)*	*(0.04)*
AR(7)	0.238	−0.007	0.091	−0.011	0.161	0.099
	(0.03)	*(0.43)*	*(0.09)*	*(0.37)*	*(0.03)*	*(0.06)*
AR(8)	0.224	−0.007	0.085	0.003	0.144	0.092
	(0.04)	*(0.42)*	*(0.10)*	*(0.46)*	*(0.04)*	*(0.06)*
AR(9)	0.213	−0.003	0.081	−0.004	0.127	0.086
	(0.06)	*(0.48)*	*(0.11)*	*(0.44)*	*(0.05)*	*(0.07)*
AR(10)	0.204	−0.005	0.079	−0.008	0.110	0.080
	(0.06)	*(0.46)*	*(0.12)*	*(0.38)*	*(0.06)*	*(0.08)*

This table shows auto-correlation coefficients. We first calculate the coefficients for each stock in our sample. The table shows cross-sectional averages. Below each auto-correlation is the fraction of stocks with an auto-correlation of opposite sign from the average. Returns are measured using the mid-point of the bid-ask spread. Inventories are measured at the end of each day. Normalized variables are described in the text. *T*-statistics are shown in parentheses. The sample period starts March-1999 and ends December-2004.

4. The trading behavior of liquidity providers

4.1. Inventory control

We begin the section by analyzing the trading behavior of two groups of liquidity provider at the individual stock-level. Table 8 reports tests of whether NYSE specialists and/or competing market makers have mean reverting trades. In order to compare net trades across trader types, we calculate the daily change of specialists' inventories and label this measure $\Delta INV_{i,t}$. For each of the 915 stocks with at least 1461 days of data, we calculate the first ten daily auto-correlation coefficients. We then report the cross-sectional average of each auto-correlation coefficient. Table 8 shows that inventories levels, $INV(\$)$, are highly auto-correlated with a 0.542 first-order coefficient. The net trades of NYSE specialists, $\Delta INV(\$)_{i,t}$, show strong mean-reversion. The first three auto-correlation coefficients are −0.322, −0.069, and −0.026 respectively. To gauge significance, we record the fraction of stocks with a correlation that is opposite in sign to the average. We find 0% of stocks have a positive $AR(1)$ coefficient when looking at $\Delta INV(\$)_{i,t}$. Combined with earlier results from Table 2, the mean-reversion indicates NYSE specialists behave in a manner consistent with theoretical models of market making. They initially buy as prices are falling or they initially sell as prices are rising. After building a position, specialists quickly undo their trades and mean-revert inventories towards target levels.

The autocorrelation coefficients shown in Table 8 indicate specialists revert their inventories back towards target levels at a faster rate than previously reported in the literature. Madhavan and Smidt (1993) report half-life of inventory positions on the order of 49 trading days. After correcting for shifts in desired target levels, their estimated half-life falls to 7.3 days. For our variable $\Delta INV(\$)_{i,t}$, an $AR(1)$ coefficient of −0.322 indicates a half-life of 1.78 days. A slightly shorter half-life is obtained when considering all ten autoregression coefficients. The difference between our results and those in the earlier paper most likely stems from differences in sample periods. Madhavan and Smidt (1993) examine data from February 1, 1987 to December 31, 1987. Our data are generated approximately fifteen years later and trading conditions have undoubtedly evolved.

Table 8 shows the net trades of competing market makers do not mean-revert. Instead, the trades of CMMs are positively and significantly auto-correlated with $AR(1)$ coefficients of 0.252. After a week/five days, the $AR(5)$ coefficients is 0.109. The normalized measures also display high levels of positive auto-correlation. As discussed earlier, the positive autocorrelation for CMMs' trading could be due to the aggregate nature of the data or due to longer holding periods.

Table 2 shows both groups of liquidity providers trade against contemporaneous price movements—they buy as prices fall and sell as prices rise. The differences in auto-correlations shown in Table 8 suggest that the liquidity providers may trade with each other following a significant rise or fall in prices.

4.2. Cross auto-correlations of liquidity providers net trades

To better understand trading between groups of liquidity providers we calculate the cross auto-correlation of net trades. We divide stock-days into those when NYSE specialist inventories are neither high nor low (i.e., in Quintiles 2, 3, or 4) and stock-days when inventories are more extreme (in Quintile 1 or Quintile 5). For each of the 915 stocks with at least 1461 days of data, we then measure the correlation of $INV_{i,t}$, $\Delta INV_{i,t+1}$, $CMM_{i,t+1}$, $\Delta INV_{i,[t+1,t+5]}$, and $CMM_{i,[t+1,t+5]}$. Table 9 reports the cross-sectional average of the correlation coefficients.

Table 9, Panel A considers stocks-days when inventories are neither high nor low. NYSE specialists still mean revert their inventories as the −0.255 correlation between $INV_{i,t}$ and $\Delta INV_{i,t+1}$ shows. The mean reversion continues over days $[t+1, t+5]$ as the −0.318 correlation between $INV_{i,t}$ and $\Delta INV_{i,[t+1,t+5]}$ shows. These results are consistent with the $AR(p)$ coefficients shown in Table 8. The net trades of all three liquidity providers are slightly positively correlated: $Corr(\Delta INV_{i,t+1}, CMM_{i,t+1}) = 0.052$. Below each average coefficient we calculate the fraction of stocks with correlation of opposite sign as the average.

The results in Table 9 change noticeably if a stock's inventory is in Quintile 1 or Quintile 5 on day t. Panel B shows the mean reversion increases to −0.565 between $INV_{i,t}$ and $\Delta INV_{i,t+1}$. The net trades of the liquidity providers become negatively correlated. For example, $Corr(\Delta INV_{i,t+1}, CMM_{i,t+1}) = -0.006$. The negative correlation becomes stronger over the following week: $Corr(\Delta INV_{i,[t+1,t+5]}, CMM_{i,[t+1,t+5]}) = -0.033$.

In summary, Tables 8 and 9 provide evidence of a "chain of liquidity provision". NYSE specialists and competing market makers each buy as prices fall and sell as prices rise. The buying behavior is stronger for specialists though we do see evidence of CMMs also buying. NYSE specialists unwind their positions quickly while the CMMs continue a trend of buying or selling. The net result is that, following a large and positive build up of inventory, specialists sell to competing market makers. Following large short inventory positions, specialists buy shares back from competing market makers.

The results from Table 9 are the likely result of heterogeneity CMMs. Some CMMs buy (sell) when the specialists buy (sell). However, there are other CMMs that want to buy (sell), but appear to arrive late to market. Having some CMMs respond slowly to stock price movements is also consistent with the autocorrelation patters seen in Table 8.

The results in Tables 8 and 9 also suggest that conditioning on the trades of two or more liquidity providers help identify times when large amount of liquidity has been provided. It is during

Table 9
Correlations of inventories and future trading variables.

	$INV_{i,t}$	$\Delta INV_{i,t+1}$	$\Delta INV_{i,[t+1,t+5]}$	$CMM_{i,t+1}$	$CMM_{i,[t+1,\ t+5]}$
Panel A: Using data from "Middle" quintiles (2, 3, and/or 4)					
$INV_{i,t}$	1.0	−0.255	−0.318	0.016	0.024
		(0.00)	*(0.00)*	*(0.40)*	*(0.39)*
$\Delta INV_{i,t+1}$		1.0	0.217	0.052	0.039
			(0.00)	*(0.28)*	*(0.24)*
$\Delta INV_{i,[t+1,t+5]}$			1.0	0.003	0.033
				(0.48)	*(0.35)*
Panel B: Using data from "Extreme" quintiles (1 and/or 5)					
$INV_{i,t}$	1.0	−0.565	−0.713	0.062	0.077
		(0.00)	*(0.00)*	*(0.26)*	*(0.25)*
$\Delta INV_{i,t+1}$		1.0	0.559	−0.006	−0.015
			(0.00)	*(0.48)*	*(0.39)*
$\Delta INV_{i,[t+1,t+5]}$			1.0	−0.045	−0.033
				(0.27)	*(0.31)*

This table shows the correlations of inventories on day t and future trading variables. The future variables are measured over day $t+1$ and over the interval $[t+1, t+5]$. Correlations are first calculated for each stock in our sample. The table shows cross-sectional averages. Below each correlation is the fraction of stocks with correlation of opposite sign as the average.

these times that return predictability may be particularly large. Our earlier double sort results (Table 7) show this to be the case.

5. Conclusion

We examine the role of liquidity providers and their impact on short run stock returns. Liquidity providers buy stocks with falling prices and sell stocks with increasing prices in order to accommodate others' demand to trade immediately. We study two types of liquidity providers: designated market makers (NYSE specialists) and competing market makers both of whose trades are identified in proprietary NYSE data. Our results find a subtle process of liquidity provision—one that depends both on horizon and stock characteristics. Today's trades of NYSE specialists and competing market makers both predict returns over day $t+1$. Portfolios of stock sorted by today's returns, however, have no predictability for returns over day $t+1$.

Portfolios of stocks sorted by specialists' inventories, CMMs' net trades, and/or returns over the past week or two weeks also predict returns on day $t+1$. Both NYSE specialist inventories and past returns help predict returns of large stocks better than small stocks—specialist predictability is strongest over the $[t+1, t+5]$ horizon while return predictability is strongest over the $[t+2, t+5]$ horizon. The net trades of competing market makers help to predict returns of smaller stocks (after controlling for the ability of specialist inventories and returns to predict returns.)

A Fama–Macbeth regression of future returns on indicator variables shows extreme trading in each of the three groups helps forecast returns. The trades of one group are not "driven out" by trades from other groups, nor by returns. It is not surprising that using trades of both NYSE specialists and competing market makers helps predict significant returns—we show 88 bp per week of predictability. Since the aggregated data from our two groups appear to be generated at different frequencies, using trades from both helps identify times when liquidity has been most provided.

Our data also highlight the difference between designated market makers and competing market makers on the NYSE. Specialists buy as prices are falling (sell as prices are rising), accumulate inventory positions, and then quickly mean-revert their positions towards target levels. The half-life of their holdings is estimated to be 1.78 days. Competing market makers also buy as prices are falling (sell as prices are risking) but do not reverse their trades within a two-week window. Instead, the CMMs engage in highly auto-correlated buying or selling runs. They end up trading with NYSE specialists as the specialists work to reduce their inventory positions.

Deviations from efficient prices may not represent profitable trading opportunities for a liquidity demanding trader for several reasons. First, the trading data on market makers is not publically available. Second, transactions costs are likely incurred on both when opening and closing a position. The fact that seemingly large predictability in returns may not yield profitable trading opportunity makes carefully defining market efficiency important for work claiming to uncover violations of efficiency.[10]

The return predictability from liquidity provision is a form of limits to arbitrage. Further study of liquidity provider risks, returns, and strategies is warranted. In addition, the implicit gains that arise from the correlation between future returns and liquidity providers past trading may be offset by losses incurred when accumulating positions.[11] Such loses could be substantial.

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[10] For a detailed examination of this point see Avramov et al. (2006).

[11] See Hasbrouck and Sofianos (1993) for a spectral decomposition of liquidity provider profitability. This methodology enables identification of the horizon of profitability for liquidity providers.

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