

Market Maker Inventories and Stock Prices

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Empirical studies linking liquidity provision to asset prices follow naturally from inventory models. Liquidity suppliers and market makers profit from providing immediacy to less patient investors, but have limited inventory-carrying and risk-bearing capacity. Similarly, limits to arbitrage arguments rely on certain market participants accommodating buying or selling pressure. These liquidity suppliers/arbitrageurs are willing to accommodate trades—and, therefore, hold suboptimal portfolios—only if they are able to buy (sell) at a discount (premium) relative to future prices. Thus, large liquidity-supplier inventories should coincide with large buying or selling pressure, which causes price movements that subsequently reverse themselves.¹

By identifying and studying the inventories of traders who are central to the trading process and whose primary roll is to provide liquidity—New York Stock Exchange (NYSE) market

makers or “specialists”—over an 11-year period, this paper contributes to a deeper understanding of inventory/asset price dynamics. The length of our sample enables us to confirm the underlying causal mechanism—liquidity-supplier inventory—behind attempts to link liquidity and stock returns through return reversals. Prior data on inventories typically cover relatively short periods of time and/or a limited number of securities. While these limitations prevented testing of inventory/price relationships at *inter-day* horizons, the microstructure literature has been quite successful in showing that order flow and inventories play an important role in *intra-day* trading and price formation.

We examine the relationship between closing market-maker (specialist) inventories and future stock prices at daily and weekly horizons. We find that specialist inventories are negatively correlated with contemporaneous returns at both the aggregate market and individual stock levels. This finding is consistent with specialists acting as dealers and accommodating buying and selling pressure. For the specialist to be compensated for taking on inventory, he must unwind positions at better prices than those prices at which the position was accumulated. Using returns calculated with quotes (to avoid bid-ask bounce), we find that a value-weighted portfolio of stocks where the specialist is long outperforms a portfolio of stocks where the specialist is short by 10.3 basis points the day following portfolio formation and 10.2 basis points the second day after portfolio formation. Returns decline steadily to 3.4 basis points at day 5. All these returns are statistically significant. At day 10, the long-short portfolio return is down to 2 basis points and is no longer statistically significant. The cumulative return of the long-short portfolio is 45.4 basis points over 10 days. While these returns seem large, specialists do not disclose their inventory positions, so predictability based on inventories comes from nonpublic information.

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¹ See Yakov Amihud and Haim Mendelson (1980), Thomas Ho and Hans R. Stoll (1981), Sanford J. Grossman and Merton H. Miller (1988), and others for inventory models that lead to reversals. Inventory reversals are empirically similar to, but on a larger scale than, reversals due to bid-ask bounce (Richard Roll 1984) and reversals following block trades (Alan Kraus and Hans R. Stoll 1978).

Because inventory data have previously been unavailable to study longer-horizon returns, researchers have constructed proxies for market-maker inventories and limited risk-bearing capacity. Proxies such as order imbalances and “liquidity shocks” capture the demand for liquidity, which the suppliers of liquidity presumably accommodate (Tarun Chordia, Roll, and Avanidhar Subrahmanyam 2002). John Y. Campbell, Sanford J. Grossman, and Jiang Wang (1993) examine how trading volume interacts with past returns in determining future return reversals. Lubos Pastor and Robert F. Stambaugh (2003) use a related measure to show that liquidity is a priced risk factor. Simple return reversals in individual stocks—Bruce N. Lehmann (1990) and others—are also related to inventory effects. Our approach of directly measuring a supply of available liquidity (i.e., specialist inventories) is complementary to these studies. This paper broadens our understanding of the complex and dynamic process of demanding and supplying liquidity by studying it from the liquidity-supplier side.

I. Inventory Data and Descriptive Statistics

Several datasets are used to construct our sample of daily specialist inventories and prices from 1994 through 2004. Center for Research in Security Prices (CRSP) data are used to identify common stocks and their trading volume, market capitalization, stock splits/distributions, closing prices, and returns. The Trades and Quotes (TAQ) database is used to identify the closing quotes. Internal NYSE data from the specialist summary file (SPETS) provide the specialist closing inventories data for each stock on each day. We refer to the specialist inventory at the end of the trading day simply as “inventory.” To remove bid-ask bounce, close-to-close returns are calculated using bid-ask quote midpoints.

The aggregate market inventory averages about \$200 million at the end of each day, but declines somewhat starting in late 2002. The volatility of the inventory levels increases over the beginning of the sample period. Aggregate inventory levels reach a maximum of \$1 billion (long) and a minimum of $-\$200$ million (short). The inventory level fluctuates with a daily standard deviation of \$137 million, and the standard deviation of inventory changes is

\$107 million. Absolute changes in the inventory position average \$77 million each day with a standard deviation of \$75 million.

Daily changes in aggregate inventory have a -0.71 correlation with contemporaneous market returns. Because inventories typically start the day above or below their average level and exhibit mean reversion, the correlation of returns over a day and inventory levels at the end of the day is somewhat lower at -0.57 . The cross-sectional mean of individual stocks’ time-series correlation between inventory levels and returns is -0.23 . The skewness of aggregate inventories (0.71) and individual stock inventories (0.75 on average) are both positive, implying that specialists take larger positive positions than negative positions.

Each day we allow for time-varying target inventory levels (Ananth Madhavan and Seymour Smidt 1993) by calculating the moving average and standard deviation of each stock’s inventory level over the past three months beginning ten days ago. We define the standardized inventory (z^{INV}) as the dollar inventory minus its mean divided by its standard deviation. The average correlation of individual stocks’ dollar inventory and standardized inventory is 0.76. The average correlation of individual stocks’ dollar inventory and returns is -0.24 , while average correlation of z^{INV} and returns is -0.25 .

II. Inventories and Future Returns

We now test another inventory model prediction—inventory levels forecast future return reversals. While, prior to this paper, there is no direct evidence of empirical support for the reversal prediction, it is commonly used to justify and examine the relationship between liquidity and prices. Table 1 shows the impact of inventories on subsequent prices. Following the standard portfolio-formation approach, we sort stocks into quintiles each day of our sample period based on two inventory measures. Panel A sorts by dollar-inventory levels and is labeled *INV*; panel B sorts by our standardized inventory measure and is labeled z^{INV} . Portfolios are formed each day and returns are calculated using closing mid-quote returns with market capitalizations as weights. We use mid-quote returns, value weighting, and quintiles to minimize the impact of small illiquid stocks.

TABLE 1

Sort quintile	Turnover (bp)	Return Stdev (%)	MktCap (\$ bn)	r_{t+1} (bp)
<i>Panel A: Sort by INV</i>				
Lo (-)	45	2.2	7.7	0.2
P2	40	2.8	2.3	2.5
P3	38	2.8	1.9	4.5
P4	42	2.4	3.0	7.6
Hi (+)	49	2.3	9.8	8.6
Hi - Lo				8.5
<i>Panel B: Sort by z^{INV}</i>				
Lo (-)	40	2.5	4.2	-0.6
P2	45	2.6	4.9	2.1
P3	46	2.5	5.8	5.0
P4	44	2.4	5.5	7.5
Hi (+)	40	2.4	4.3	9.7
Hi - Lo				10.3

Sorting by dollar inventory (panel A) puts the highest turnover, least volatile, and largest market capitalization stocks in the outer quintiles. This suggests that inventory is more manageable in larger, more active stocks, so specialists are willing to take larger positions in these stocks. While such a finding may be expected, it leads the quintile portfolios to have different stock characteristics. Sorting by the standardized inventory measure (z^{INV}) helps to distribute market capitalization more evenly across quintiles.

Both inventory sorts provide qualitatively similar result in terms of predicting returns. The low-inventory portfolios have next-day returns close to or below zero, while the high-inventory portfolios have returns between 8 and 10 basis points the next day. Therefore, a portfolio long on the highest inventory stocks and short the lowest inventory stocks yields 8.5 basis points (panel A) and 10.3 basis points (panel B) the next day. Both have Newey-West t-statistics greater than nine. The raw returns demonstrate that the inventory positions of liquidity providers forecast future prices. When sorting on dollar inventory, large firms are in the outer portfolios, indicating that the inventory/reversal effect is not a small stock phenomenon. Given that we are trying to isolate inventory effects from other stock characteristics, we focus on the standardized inventory measure for the rest of the paper (although using the dollar inventory measure yields similar results.)

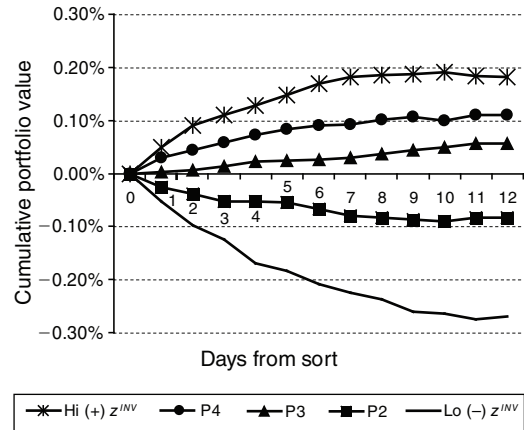


FIGURE 1. POST-INVENTORY SORT PORTFOLIO RETURNS

To quantify the duration of inventory effects on prices, Figure 1 shows the returns net of the market for the 12 days after portfolio formation based on standardized inventory. The highest inventory portfolio (P5) increases by 5 basis points on the first day, 4 basis points on day 2, and asymptotes to 19.0 basis points. The lowest inventory portfolio (P1) declines by 5 basis points each of the first 2 days and decreases by approximately 3 basis points on days 3 through 6, and ultimately declines to 26.4 basis points. The cumulative 5- and 10-day return differences between the long- and short-inventory portfolios are 33.0 and 45.4 basis points, respectively. Controlling for market returns, the Fama-French size factor, the Fama-French market-to-book factor, and a momentum factor have little effect on the predictability results. Each of the first five days' risk-adjusted return (intercept, often referred to as "alpha") is significant. The tenth day's alpha remains positive at 2.1 basis points, but the t-statistic is only 1.8.

The asymmetry between the returns of the highest and lowest portfolios suggests that the specialist's willingness to take larger long positions than short positions translates into differences in future prices. The largest positive positions lead to less mean reversion than the most negative positions. The difference in returns between the highest inventory and second highest inventory position is also smaller

than the difference in returns between the lowest inventory and second lowest inventory position. When the specialist is short, other traders must sell for the specialist to reduce his position (buy back shares). Traders who do not already own the stock face short-sale constraints, potentially limiting the number of sellers.²

Our findings that long (short) inventories coincide with negative (positive) returns and forecast positive (negative) returns the next day are consistent with inventory and liquidity-provision models. To examine the pre- and post-formation price changes, Figure 2 extends the returns in Figure 1 back six days in time by adding the portfolio formation day as well as the prior five days. Note that the ordering of the high- and low-inventory portfolios is switched when compared with Figure 1. The Y-axis measures cumulative returns (prices), which means the highest inventory portfolio is on top in Figure 1, while the highest inventory portfolio is on the bottom in Figure 2. The graphs are consistent with the specialists acquiring their positions as they accommodate the liquidity demands of other traders. The specialists then unwind their positions as prices reverse.

The highest and lowest inventory portfolios exhibit asymmetry prior to formation with the high-inventory portfolio falling 1.29 percent and the lowest portfolio rising 1.48 percent. As in Figure 1, the highest portfolio then reverses 19.0 basis points, while the lowest portfolio reverses 26.4 basis points. The pre- and post-formation returns show that price changes prior to portfolio formation are many times larger than the reversal. Just as the asymmetry between the post-formation returns of the longest and shortest inventory positions does not naturally arise in inventory models, neither do the asymmetric price movements in the pre-formation periods. The asymmetry in long- and short-inventory size and pre- and post-formation returns points

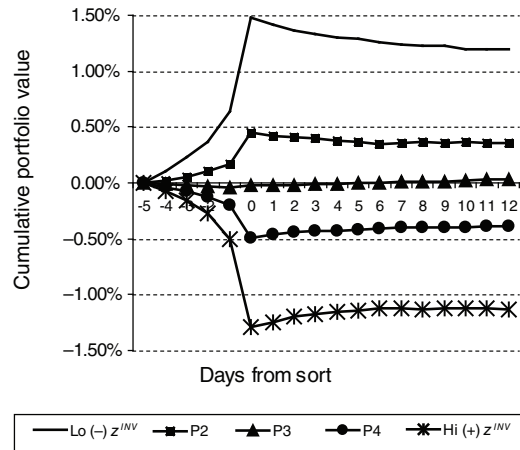


FIGURE 2. PRE- AND POST-INVENTORY SORT PORTFOLIO RETURNS

to the specialist preferring long positions to short positions. This preference leads to smaller downward price changes by day 0 and smaller subsequent return reversals over days 1 to 12.

While our results show that the marginal additional dollar of inventory appears profitable, most of the large long (short) inventory positions occur on days when prices fall (rise). Prices then show small mean reversion relative to the pre-formation return, making these large inventory positions appear unprofitable overall for the specialist.³

Finally, we examine “day-of-the-week” effects in the inventory induced reversals. The predictable reversal (over a week) of the high-inventory minus low-inventory portfolio is 50 percent higher when sorting at the end of the calendar week versus on Wednesdays. The greater predictability at the end of trading weeks is due to the specialists needing to hold suboptimal portfolios for a longer period of time—over the weekend as opposed to overnight.

² Specialists often give a different explanation for the long-short asymmetry. They claim to be more sensitive to preventing downward stock price movements and, therefore, take large long positions when others investors are net sellers. This explanation appears less plausible because there is asymmetry in inventory levels, but not in changes in inventory.

³ This is consistent with the Joel Hasbrouck and George Sofianos (1993) evidence that the specialists make most of their money at short horizons and are not profitable at longer horizons.

III. Conclusion

Liquidity and limits to arbitrage arguments regarding asset prices rely on the idea that certain market participants accommodate buying or selling pressure. These liquidity suppliers/arbitrageurs will hold suboptimal portfolios only if they are compensated by favorable subsequent price movements. Thus, when inventories are large, liquidity suppliers have deviated from their optimal portfolios. Associated price changes should subsequently reverse. Using a unique 11-year sample of NYSE specialist inventories, this paper is able to test and confirm the underlying causal mechanism—liquidity supplier inventory—behind attempts to link liquidity and stock returns through return reversals. Consistent with specialists acting as dealers and temporarily accommodating buying and selling pressure, we find that specialist inventories are negatively correlated with contemporaneous returns at both the aggregate market level and individual stock level. We find that specialists are compensated for inventory risk by return reversals.

Substantial work remains to be done in understanding the dynamics of specialist inventories. Better knowledge of these dynamics should help refine analysis of inventories and prices. First, the length of our sample can allow for a detailed study of the mean reversion in inventories both cross-sectionally and over time. Second, individual specialists trade a number of stocks referred to as a “panel.” Inventory and return dynamics within a given panel may be important for risk management. Third, specialists are part of larger firms. Inventory and return dynamics within a given firm may be important for risk management. A deeper understanding of market-making firms and the inventories of other financial intermediaries may generate additional hypotheses regarding the dynamics of trading and prices.

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