Correlated Portfolio Inventory Risk of Liquidity Providers: Frictions and Market Fragility

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Abstract

We investigate, for limit order book equity markets, how trading, liquidity provision, and the overall market quality in one security are influenced by correlated inventory risk exposures of liquidity providers to other securities in their portfolios. We find strong support for Ho and Stoll (1983). Our results are also consistent with large and correlated portfolio inventories worsening different measures of market quality – including bid-ask spreads and pricing errors – and increasing the number and likelihood of extreme price movements and transitory jumps in stock returns. We accordingly highlight a significant but often overlooked source of market frictions, contagion, and fragility.

Keywords: Liquidity Providers, Inventories, Limit Order Markets, Market Quality, Fragility

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1. Introduction

Limit order book ("LOB") markets are now the dominant exchange structure for equity trading globally. Unlike affirmatively obliged old-world NYSE Specialists or London/NASDAQ market makers, the *de-facto* 'market-maker' in LOB markets emerges endogenously and voluntarily.[1] We label such a *de-facto* 'market-maker' as a 'voluntary liquidity provider' (hereafter "VLP").[2] Typically, a VLP simultaneously participates in multiple securities. As modeled by Ho and Stoll (1983) for markets with multiple liquidity providers, possibly with heterogeneous beliefs, a VLP's trading and liquidity provision in a stock would be a function of her "*equivalent portfolio inventory*" in that stock – rather than just her inventory in that stock – where this *stock-specific* equivalent portfolio inventory (hereafter "correlated portfolio inventory" or just "portfolio inventory" when the context is clear) includes the effect of her correlated inventory risk exposures from the other stocks in her overall portfolio.[3] Hence, a stock's liquidity would be a function not only of liquidity providers' inventory in the stock, but also of their inventory in *other correlated* securities. The management of these liquidity providers' correlated portfolio inventories could arguably be a significant source of contagion-induced fragility, since liquidity shocks in one security can propagate to another security through these channels.

Notwithstanding the intuitive appeal of Ho and Stoll (1983), Naik and Yadav (2003a) – the only other study (to our knowledge) to test Ho and Stoll (1983) in the context of correlated portfolio inventories – find that market-maker firms in the old pre-1997 pure dealer market on the London Stock Exchange overlooked inventory risks in correlated securities at the overall firm level, and argued that this could be due to organizational agency costs, difficulties in real-time communication amongst the firm's traders in a telephone-based trading environment, and their affirmative obligation constraints to always stand ready to provide liquidity at the level of individual stocks. On the other hand, VLPs in today's LOB markets' are typically not constrained by affirmative obligations, and positions' data across stocks is continually accessible contemporaneously in real time. Hence, one should expect to find support for Ho and Stoll (1983) from a liquidity provision perspective at the trading unit level. However, in view of the voluntary nature of market-making in today's LOB markets, VLPs could also

[1] Some markets have designated market makers (Anand and Venkataraman, 2016) that can involve obligations and provide value in certain circumstances (Menkveld and Wang, 2013; Bessembinder, Hao, and Zheng, 2015).
[2] A VLP is, in aggregate, a net liquidity provider, trading on its own account with incoming buy and sell orders, bearing the cost and the risk of unbalanced inventory exposures, and earning the premium for doing so (Anand and Venkataraman, 2016; Menkveld, 2013; Glosten, 1994). Our VLP is economically similar to the ELP ("E" for endogenous) in Anand and Venkataraman (2016), but we used "VLP" since our VLP always acts voluntarily (as is common in most LOB markets), while their ELP analysis is anchored also to designated market makers.
[3] It is important to note that the *equivalent portfolio inventory* is ***not*** the same as the unconditional sum of the inventories of the stocks in the portfolio. It is *stock-specific* in as much as it is the overall portfolio inventory after accounting specifically for the extent to which the portfolio stocks are *correlated* with that particular stock.

deviate from a pure market-making strategy and adopt a more information-driven strategy. Specifically, VLPs could learn about a security's fundamental value from prices of other securities with correlated returns (Pasquariello and Vega, 2013; Cespa and Foucault, 2014). In such a scenario, they could potentially take similar positions across correlated stocks rather than the offsetting positions predicted by Ho and Stoll (1983). Therefore, establishing the net influence of correlated inventories on the trading behaviour of VLPs is not necessarily unambiguous, and requires empirical analysis. We accordingly investigate the cross-security implications of VLPs' portfolio inventory management in LOB markets with data on VLP trading accounts.

We find the following main results. First, in accordance with the predictions of Ho and Stoll (1983), VLPs in LOB markets do manage their inventory risk on a *portfolio* basis in addition to a stock-by-stock basis. Second, a VLP's trading and order placement strategy is significantly influenced by her inventory in the other correlated securities in her portfolio. Third, consistent with information-driven objectives, the offsetting influence of correlated securities is less pronounced for VLPs whose trading is more likely to be driven by informational strategies. Finally, our results are consistent with the hypothesis that, as a security's liquidity worsens, it experiences greater cross-security price pressures and episodes of market stress when VLP positions in correlated securities are large and undispersed.

Our study contributes to several streams of the literature. First is the literature on the effect of dealer inventories on their trading behavior. For example, Madhavan and Smidt (1993), Manaster and Mann (1996), Hansch, Naik, and Viswanathan (1998), Reiss and Werner (1998), and Naik and Yadav (2003b) document that differences in inventories across dealers on the LSE affect their trading with customers and with other dealers. However, these studies only consider the effect of individual stock-level inventories. In contrast, our focus is on market-makers' *portfolio-based* inventory control that incorporates correlated inventories in other stocks.

Naik and Yadav (2003a) is, to our knowledge, the only directly relevant existing study on market-makers' portfolio-based inventory control; and our results are in sharp contrast with their results. One reason for the difference in results could be because their data was only at the *centralized* level of the whole (market-making) firm, not at the level of individual trading units within the firm, and these firms were so large that only about 15 market-making firms were responsible for all London market trades. The telephone-based OTC market structure would have also made it difficult to share real-time positions' data across stocks and across the firm's trading units. Naik and Yadav (2003a) were hence unable to test whether correlated portfolio inventories drove the primary-level decision-making of a trading unit within the firm, the level at which Ho and Stoll (1983) should apply with minimal confounding influences. In this paper, we use data that separately identifies each VLP trading account, and our VLPs are able to instantly trade electronically thereby enabling smooth, real-time monitoring and management of positions across stocks. Hence, we can cleanly test the predictions of Ho and Stoll (1983) for the trading of liquidity providers, and our results turn out to be strongly supportive.

Second, our study significantly contributes to our understanding of the effect of correlated portfolio inventories on market quality and fragility. There has been great regulatory concern[4], in line with academic evidence, that LOB markets remain uncomfortably dependant on stability in the supply of liquidity from VLPs. This can be problematic, especially in peak load and stress periods.[5] In spite of this heightened regulatory concern, there is very little we know about the determinants of liquidity-induced market fragility in LOB markets. Papers that study inventory effects have typically only considered NYSE specialists' or aggregate brokerage houses' inventory risks (e.g. , Comerton-Forde et al., 2009; Coughenour and Saad, 2004). However, since NYSE specialists are affirmatively obligated to supply liquidity, studies focusing on NYSE specialists cannot answer questions about the influence of purely *voluntary* liquidity provider inventories on market fragility. When we turn to LOB markets, most empirical studies have ignored inventory costs altogether.[6] But, there are some notable exceptions. Recent studies by Anand and Venkatraman (2016), Kirilenko et al. (2017), and Getmansky et al. (2018) show that VLPs turning from liquidity providers to liquidity demanders due to unsustainable levels of inventory imbalances is an important precursor to episodes of market fragility. Our results show that, along with stock-level inventories, large correlated portfolio inventories significantly increase the likelihood of market fragility, measured using extreme price movements and transitory jumps in stock returns. VLPs' correlated portfolio inventories are a significant determinant of LOB market fragility.

Furthermore, while correlated trading of liquidity providers has received recent attention (e.g. Chabound et al, 2014), we know very little about the impact of such trading on market quality. Our result that episodes of market fragility are more likely when portfolio inventories are less dispersed across VLPs contributes to our understanding of the adverse effects on market fragility of correlated trading by liquidity providers. Accordingly, our paper has significant policy relevance in informing exchange and regulatory perspectives on affirmative obligations and designated market-making. Anand and Venkataraman (2016) contribute to academic and regulatory understanding here by investigating correlated trading of different VLPs. We do so by investigating VLPs' management of correlated inventory exposures across different securities.

Finally, our results provide a cleaner understanding of a supply-side channel for cross-security price pressures. Studies that examine the effect of inventories on price pressures have typically focussed only on stock-specific inventories (e.g., Hendershott and Seasholes, 2008; Hendershott and Menkveld, 2014). We build on this literature to show that, even after controlling for the effect of stock-level inventories, VLP positions in other correlated securities create significant cross-security price pressure. Another strand of literature uses aggregate order imbalance (OIB) data to examine cross-security price pressures (e.g., Andrade, Chang and Seasholes, 2008; Pasquariello and Vega, 2013; Friewald and

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[4] See, for example, CFTC-SEC Flash Crash Report: http://www.cftc.gov/ucm/groups/public/@aboutcftc/documents/file/jacreport_021811.pdf.
[5] See, for example, Bessembinder, Hao and Zheng (2015), Anand, Tangaard, and Weaver (2009), Menkveld and Wang (2013), and Raman, Robe, and Yadav (2018a, 2018b).
[6] See, for example, Biais et al. (1995), Hall and Hautsch (2004), and Ellul et al. (2007).

Nagler, 2019). Given the lack of granular inventory data, these studies are unable to directly test the channels through which price pressures propagate across stocks. Cross-security price pressures could be brought about by the portfolio inventory management of liquidity providers and/or the portfolio rebalancing of liquidity demanders.[7] It would be difficult to distinguish between these two sources while using only aggregate order imbalance data. In contrast, since we accurately track VLP inventories across stocks, and simultaneously control for other market-wide variables, our results provide a clearer picture of the precise role of portfolio inventory management of intermediaries in the transmission of price pressures across stocks.

In order to test the extent and the consequences of a liquidity provider's portfolio inventory management, we need to be able to identify each trader, and do so with a trader code that does not change for different stocks. Such trader identification is not easily provided by Exchanges. The data we use has been provided by the National Stock Exchange (NSE) in India, currently the second largest equity market globally on the basis of the total number of trades (as per World Federation of Exchanges website.) Besides complete information on trades and orders, our proprietary data includes masked trader identification, enabling us to calculate inventories of each trader in the market over time and across stocks. Specifically, our sample comprises all 50 stocks in NSE's NIFTY-50 index over a three-month period from April to June 2006. Access to more recent data was not forthcoming. As in the case of Anand and Venkataraman (2016), algorithmic trading was not allowed during our sample period as well. Given that portfolio-driven trading should be considerably easier and quicker to execute with algorithmic trading, each of our results should arguably be even stronger in presence of computerized decision-making and trade execution. Our results show that, even in the absence of algorithmic and high-frequency trading, management of correlated portfolio inventories by VLPs is a significant source of market fragility, thereby contributing to our understanding of the inherent fragility associated with LOB markets with voluntary liquidity suppliers.

We document several interesting results. First, VLPs' portfolio inventories mean revert significantly – more than 30% – faster than ordinary, stock-level inventories. Furthermore, consistent with the central predictions of the Ho and Stoll (1983), our analysis of order imbalances and order placement decisions show that a VLP is significantly more likely to place sell (buy) orders than buy (sell) orders in a stock to offset the excess positive (negative) correlated inventory risk exposure in the rest of her portfolio.

Second, we find that correlated portfolio inventory imbalances matter particularly when these imbalances are large, when stock returns are highly volatile, or when VLPs suffer abnormal losses in their portfolio holdings. Interestingly, consistent with the information hypothesis, we find that portfolio

[7] Several papers find evidence of supply-side (Coughenour and Saad, 2004; Comerton-Forde et al., 2010; and Karolyi et al., 2012) and demand-side (Koch, Ruenzi and Starks, 2015) sources of commonality in liquidity.

inventory imbalances matter significantly less for VLPs whose trading is more likely to be driven by informational reasons, relative to those who may be trading purely for market-making reasons.

Third, our panel regressions show that market liquidity improves when the variation in VLP correlated portfolio inventory levels across different VLPs is high. These results indicate that bid-ask spread in a stock would reduce when VLPs' inventories in other correlated stocks are more dispersed, because VLPs significantly long in these other stocks would reduce the ask prices in the stock and VLPs significantly short in these other stocks would increase the bid prices in the stock. Accordingly, we further find that greater aggregate accumulated positive (negative) portfolio inventory of VLPs is associated with greater depth on the sell-side (buy-side) of the order book than the buy-side (sell-side). Furthermore, consistent with predictions of Brunnermeier and Pedersen (2008) and Gromb and Vayanos (2002), we also find that bid-ask spreads worsen when the magnitude of VLPs' aggregate portfolio inventories are relatively high. These results continue to hold even after we control for measures of market-wide liquidity and informed trading.

Fourth, results from the Kalman-filter analysis of our state-space model show that correlated portfolio inventories are also a significant source of price pressures. After controlling for the effect of stock-level inventory, a one-standard deviation increase in portfolio inventories decreases returns by 5.4 basis points, which is almost double the average bid-ask spread. The effect of portfolio inventories is particularly high during periods of low dispersion of VLP portfolio inventories across different VLPs.

Finally, we find that liquidity providers' portfolio inventories influence the likelihood of market fragility. We identify episodes of market stress using two measures: extreme price movements (Brogaard et al., 2018) and transitory jumps in stock returns (Lee and Mykland , 2008). The likelihood and the number of extreme price movements or jumps in stock returns significantly increase with the magnitude of aggregate correlated portfolio inventories, and decrease with the dispersion of these portfolio inventories across different VLPs. A one-standard deviation increase (decrease) in the magnitude (dispersion) of aggregate portfolio inventories is associated with an increase (decrease) in the odds of observing an extreme price movements episode in the next time period by a factor of 14 (by 74%); and with an increase (decrease) in the odds of observing a transient jump in stock returns by about 44% (78%). Since extreme price movements and jumps in stock returns could also be due to information spillovers from other stocks, we control for market-wide informed trading in all our analyses. Further, to mitigate the concerns of reverse causality, wherein extreme price movements or transient jumps trigger traders to rebalance their portfolio and reduce portfolio inventories, we further employ vector autoregressive regressions. Consistent with our panel regression results, the impulse response functions show that EPMs and transient jumps in stock returns are higher in number following periods of large and correlated portfolio inventories.

Overall, the bottom-line view that emerges from our results is that, while the management of correlated portfolio inventories maximizes intermediaries' utility and capacity for liquidity provision, it is also a source of significant market frictions, contagion, and liquidity fragility.

2. Hypotheses

In this section, we develop hypotheses relating to the effect of correlated portfolio inventory imbalances on trades and order placement strategies, liquidity and market fragility.

2.1. Trades, orders, and inventories

One of the central predictions of inventory models is that, in competitive markets, a liquidity provider with an imbalanced inventory will post aggressive quotes, increase her chances of executing with the incoming order flow, and thereby correct the inventory imbalance. For example, a liquidity provider with the highest abnormal inventory (relative to the median trader-inventory) will be most competitive on the sell-side of the order book, reduce inventory imbalance, and continue to do so till she reduces her inventory. Once the inventory is reduced, the trader's aggressiveness also declines. Such a sequence of events should result in observable mean reversion of trader inventories. More importantly, according to Ho and Stoll (1983), VLPs should correct for imbalances in their correlated portfolio inventory rather than in ordinary inventory. While the mean reversion in single securities inventory has been documented in the literature (Madhavan and Smidt, 1991; 1993; Hasbrouck and Sofianos, 1993; Hendershott and Menkveld, 2014), we hypothesize a significant mean-reversion in trader-level correlated portfolio inventory. Furthermore, we expect a significantly greater rate of mean reversion in these portfolio inventories than in ordinary stock-level inventories.

H1a: There is significant mean reversion in liquidity providers' correlated portfolio inventories; and this mean reversion in portfolio inventories is greater than the mean reversion in ordinary inventories.

We also expect that order placement decisions will be driven by imbalances in this portfolio inventory rather than by imbalances only in stock-level inventory. Following the same logic, a high abnormal inventory triggers a VLP to submit aggressive orders that lead to reduction of inventory. Studies, such as Reiss and Werner (1998) and Hansch, Naik, and Viswanathan (1998), have found empirically that dealers with long positions are more likely to execute buy market orders; and that those with short positions, sell market orders.

If a VLP manages correlated portfolio inventories, we expect high abnormal portfolio inventory to have a significant impact on order submission strategies as well. Specifically, we consider three possible order placement states. One, the VLP prefers the buy-side, and has limit orders only on buy-side of the book. Two, the VLP prefers the sell-side, and has only sell orders posted. Three, the VLP is indifferent between the two sides of the limit order book, wherein the VLP either places orders on both sides of the book or is absent from both. According to Ho and Stoll (1983), the probability of a VLP being in the second (first) order placement state should increase (decrease) with an increase in correlated portfolio inventory.

H1b: Sell (buy) orders and trades are more (less) likely following positive (negative) excess liquidity provider's correlated portfolio inventory.

However, unlike NYSE specialists, the VLPs in LOB markets can shift strategically from being pure market-makers to trading for information or speculative reasons. For example, information-based trading could be arbitrage-related, or arise from information in the order-flow. VLPs could learn about a security's fundamental value from prices of other securities with correlated returns and trade in the direction of an information signal (Pasquariello and Vega, 2013; Cespa and Foucault, 2014). In such a scenario, traders may take similar positions in correlated stocks, and, thereby, reduce the degree of mean reversion in portfolio inventories. Hence, the degree of mean reversion in portfolio inventories would decrease when liquidity providers take similar positions in correlated securities for informational or speculative reasons and the degree of mean reversion would increase when they trade for market-making related reasons. While the estimated degree of mean reversion in portfolio inventories is the net effect of such informational and market-making trades, the relative importance of these two types of trades would vary across the cross-section of liquidity providers. The most informed of VLPs are most likely to trade for informational reasons. Hence, we expect to observe a lesser degree of mean reversion in their correlated portfolio inventories than in the correlated portfolio inventories of other VLPs.

H1c: The degree of mean reversion in correlated portfolio inventories is lesser for the most informed of VLPs, who are more likely to trade for informational reasons relative to other VLPs.

Similarly, traders who trade more for purely liquidity provision/market-making reasons, are more likely to submit sell (buy) orders and trades following positive (negative) excess portfolio inventory.

H1d: The probability of a sell (buy) order that follows positive (negative) correlated portfolio inventory is lower for the most informed of VLPs.

2.2. Market quality and portfolio inventories.

Recent papers (e.g., Kyle and Xiong, 2001; Gromb and Vayanos, 2002; Anshuman and Viswanathan, 2005; Garleanu and Pedersen, 2007; Brunnermeier and Pedersen, 2008) have related the magnitude of inventory positions of liquidity providers to market quality. Generally, these models predict that when liquidity providers face inventory risk or capital constraints, they tend to provide less liquidity. Bid-ask spreads increase to compensate for bearing the risk. Liquidity providers' quoting strategies would go towards reduction of the magnitude of inventories in order to reduce the constraints or risk that those inventories impose on them. Hence, positive aggregate inventories across VLPs would reduce liquidity supply on the buy side of the LOB while negative aggregate inventories would reduce liquidity supply on the sell side. This leads to a significant depth imbalance of LOB markets. Finally, large abnormal inventories are causes of price pressures – a transitory price impact allowing the liquidity provider to liquidate his initial position and reduce inventory (Stoll, 1978; Ho and Stoll, 1981; 1983; Grossman and Miller, 1988; Hendershott and Menkveld, 2014). Price pressures, in turn, lead to more return reversals. In the context of the aforementioned intuition, we expect correlated portfolio inventory management to lead to a negative relation between the magnitude of correlated portfolio inventories and measures of market quality: specifically, market liquidity and magnitude of price pressures.

H2a: Market quality – liquidity and magnitude of price pressures – worsens with higher magnitude of liquidity providers' aggregate correlated portfolio inventories.

In markets where liquidity providers compete with each other, dispersion of inventories across VLPs is another key characteristic affecting market quality. Models of competitive markets (e.g. , Biais, 1993; and Ho and Stoll, 1980 and 1983) predict that as inventories of liquidity providers diverge, extreme long traders reduce ask prices and extreme short traders increase bid prices, thereby reducing the bid-ask spread – i.e., greater the dispersion in inventories, smaller the bid-ask spreads. Manaster and Mann (1996) find mixed evidence for this in the FX futures market. To the extent liquidity providers manage portfolio inventories rather than just individual security inventories, we accordingly expect greater dispersion in portfolio inventories to decrease bid-ask spreads in a stock.

When VLPs' inventories are dispersed, random trading imbalances also lead to lower non-informational transitory price impact (Andrade, Chang and Seasholes, 2008). Accordingly, we expect that higher dispersion in inventories in other correlated stocks across VLPs also reduces magnitude of transient pricing errors.

H2b: Market quality – liquidity and magnitude of transient pricing errors – improves with greater dispersion of liquidity providers' correlated portfolio inventories.

2.3.Stressful episodes and trader inventories

Another important characteristics of market quality is the incidence of extreme price movements and flash crashes. They typically happen when liquidity providers withdraw liquidity from the market in anticipation of an adverse event or due to some sort of capital constraints (e.g. , Kirilenko et al., 2011; Getmansky et al., 2018). When the magnitude of aggregate inventories of VLPs is large, capital constrained liquidity providers are less willing to post limit orders on the side that lead to further increase of their inventories. Large aggregated inventory means that a majority of liquidity providers have imbalances in inventories in the same direction. This increases a probability of liquidity withdrawal and hence increases the likelihood of extreme price movements. Therefore, we hypothesize a positive relation between the magnitude of VLP inventories and the probability of stressful episodes.

H3a: Likelihood of stressful episodes increases with the absolute value of the liquidity providers' aggregate correlated portfolio inventories.

Following the same logic as in the previous hypotheses, an increase in the dispersion of inventories across the liquidity providers would significantly reduce the chance of an extreme price movement. As inventories of liquidity providers significantly diverge from each other, extreme long traders are keen to reduce their inventory and extreme short traders are keen to increase their inventory. Therefore, dispersed correlated portfolio inventories of intermediaries are likely to mitigate the possibility of a stressful episode, such as periods of extreme price movements or periods of transient jumps in stock prices.

H3b: Likelihood of stressful episodes decreases with the dispersion of liquidity providers' correlated portfolio inventories.

3. Data

NSE was created in 1994 as part of major economic reforms in India. It operates as pure electronic limit order book market, and uses an automated screen-based trading system called National Exchange for Automated Trading (NEAT), which enables traders from across India to trade anonymously with one another on a real-time basis using satellite communication technology. NSE was the first exchange in the world to use satellite communication technology for trading. As per 2019 Annual Report of the World Federation of Exchanges, benchmarked on the basis of the total number of trades in 2018, NSE is the second largest equity market in the world irrespective of market structure, just behind Shenzhen Stock Exchange, with the NASDAQ or NYSE more than 30% lower.[8] NSE's order books accommodate all the standard types of orders that exist internationally in order-driven markets, including limit orders, market orders, hidden orders, stop-loss orders, etc. Limit orders can be continuously cancelled or modified without any incremental fees. NSE operates a continuous trading session from 9:55 am until 3:30 pm local time. The tick size is INR 0.05 (less than USD 0.01). Outstanding orders are not carried over to the next day. There is no batch call auction at the beginning of the trading day. The opening price is also determined by pure order matching.

Our sample consist of all the 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. The sample period is from April 1 through June 30, 2006, covering 56 trading days. Our choice of sample period is governed by the availability of proprietary data that includes the coded identity of each VLP. Table 1, Panel A presents summary statistics on the trading characteristics of the sample stocks over the sample period. The mean market capitalization of the 50 stock in the sample is \$7 billion, indicating these are relatively large stocks. There are, on average, 1,303 trades every 30 minutes, or approximately 43 trades per stock per minute. There are, on average, 1,678 order submissions per stock every 30 minutes, or about 56 order submissions per stock per minute. Further, the bid-ask spread, estimated from the order book and expressed as a ratio of the mid-quote, is about 3 basis points on an average. In sum, the 50 stocks that make up our sample are relatively large and liquid stocks.

Insert Table 1 about here

The dataset provides complete information of trades and orders that enables the reconstruction of the order book to obtain best quotes and depth information. More importantly, the dataset also

[8] Even in 2006 (the sample year of this study), NSE was similarly ranked at or near the top by number of trades across all equity markets.

provides identification codes of traders for all the orders and trades in the dataset, thereby enabling us to track trader inventories over time and across stocks.

While there are over 1.2 million traders in the dataset, this paper focuses only on VLPs. A VLP follows trading strategies primarily directed at harvesting bid-offer spread revenues by supplying liquidity through standing limit orders to buy and sell, using liquidity-demanding marketable orders as needed to minimize inventory risk exposure, participating on both sides of the book as expedient, often without pre-meditated directional bets, and turning over inventory as often as is optimal. As discussed in recent studies (e.g., Kirilenko et al, 2017; Menkveld, 2013; Brogaard, Hendershott, and Riordan, 2014), primary characteristics of voluntary intermediaries are that they carry very little overnight inventory and that they trade actively and provide liquidity in large number of transactions. Accordingly, to identify VLPs, similar to Kirilenko et al. (2017), we first filter for traders with an average *Churning Ratio* (ratio of end-of-day inventory and daily trading volume) of less than 5%. Next, we require that the trader must provide liquidity to large number of transactions. As a base case, we select 100 traders with highest (passive) limit order book volume.[9]

Table 1, Panel B presents descriptive statistics for the VLPs – the statistics are calculated for each of the 100 VLPs, first by stock and then averaged across the 50 stocks in the sample. As seen in the table, these selected VLPs account for almost 40% of all limit orders submitted, and for more than 57% of all trades in a median stock. Their presence is equally significant when we calculate their activity in terms of the volume of trades and orders – they account for almost 50% of all trading volume and 47% of all limit order volume. Clearly, these VLPs have a significant presence in the NSE limit order book. Further, consistent with the VLPs being the de-facto (voluntary) market makers, their average and median *Churning Ratios* are 3.02% and 0.00% - these numbers imply that the VLPs invariably carry over very little, if not none, of their daily inventory in a stock over to the next trading day. Finally, as indicated by their average *Aggressiveness*, the ratio of a VLP's daily aggressive trading volume (trades where the VLP's places the aggressive order) and daily trading volume, they provide liquidity slightly more than they demand it.[10] Overall, the descriptive statistics indicate that the VLPs display the required characteristics of carrying very little overnight inventory and of providing large amounts of liquidity.

4. Empirical Tests

4.1. Construction of inventory series

Trader's inventory series are constructed along the lines of Hansch, Naik and Viswanathan (1998) and Naik and Yadav (2003a). We construct standardized inventories for each trader and stock.

[9] To ensure that our results are not driven by the arguably arbitrary numbers of traders selected, in the robustness section, we analyze 150 and 300 traders with highest (passive) limit order book volume. The results remain qualitatively similar, and are available in Internet Appendix B.
[10] This is consistent with the evidence in Kirilenko et al. (2017) for index futures contracts traded on the CME.

Such a standardization has two benefits. One, traders with different risk aversion and capital constraints can now be compared with each other. Two, as shown in Naik and Yadav (2003a), standardized inventories do not depend on the initial inventory levels; hence, not knowing the initial inventory of the traders is not an impediment to the analysis. Also, since VLPs invariably carry little (if any) inventory overnight, not knowing the initial inventory levels is even more inconsequential for our analysis. Let $Q_{j,i,t}$ denote the level of inventory of trader j in stock i at time t denominated in rupees. All inventories are calculated at 30-minute intervals. Now, standardized inventory, $inv_{j,i,t}$, is calculated as follows:

$$inv_{j,i,t} = \frac{Q_{j,i,t} - \bar{Q}_{j,i}}{stdev(Q_{j,i})}, \quad (1)$$

where $\bar{Q}_{j,i}$ is trader j's the sample average inventory in stock i, and $stdev(Q_{j,i})$ is the sample standard deviation of trader j's inventory in stock i.

We calculate for each stock i the portfolio inventory as the equivalent inventory in Ho and Stoll (1983). This is the aggregate inventory including all stocks in the portfolio weighted by their respective "betas" with respect to that stock. This captures the idea that liquidity providers would put more emphasis on managing inventories of stocks whose returns covary more with the returns of stock i. Specifically, portfolio inventory series, $PQ_{j,i,k}$, for each trader j and stock i is defined follows:

$$PQ_{j,i,t} = \sum_{k=1,k\neq i}^{k=50} \beta_{i,k}\, Q_{j,k,t}, \quad (2)$$

where $\beta_{i,k}$, is the regression co-efficient obtained from a regression of 30-minute returns of stock i on stock k. We also define total portfolio inventory , $TPQ_{j,i,k}$, for each trader j and stock i as

$$TPQ_{j,i,t} = Q_{j,i,t} + PQ_{j,i,t}. \quad (3)$$

Next, similar to ordinary inventories, we also standardize portfolio inventory variables:

$$pinv_{j,i,t} = \frac{PQ_{j,i,t} - \overline{PQ}_{j,i}}{stdev(EQ_{j,i})}, \quad (4)$$

$$tpinv_{j,i,t} = \frac{TPQ_{j,i,t} - \overline{TPQ}_{j,i}}{stdev(TPQ_{j,i})} \quad (5)$$

These inventory series are used in regressions to establish the incremental effect of a trader's inventory in the rest of her portfolio. Finally, consistent with earlier literature, we also employ relative inventories, which are calculated as a trader's standardized inventory minus the median standardized inventory across the VLPs in a stock, in our analyses. For example:

$$invrel_{j,i,t} = inv_{j,i,t} - median(inv_{i,t}^{LOTs}), \quad (6)$$

$$pinvrel_{j,i,t} = pinv_{j,i,t} - median(pinv_{i,t}^{LOTs}) \quad (7)$$

where $median(inv_{i,t}^{LOTs})$ and $median(pinv_{i,t}^{LOTs})$ are the median standardized ordinary and portfolio inventories across the VLPs in stock i at time t. $pinvrel_{j,i,t}$ is defined analogously.

4.2. Mean reversion in trader inventories

We test our Hypothesis H1a by estimating the coefficient of mean reversion in VLPs' relative ordinary and relative portfolio inventories using the following autoregressive models:

$$\Delta invrel_{j,i,t} = \alpha_0 + \alpha_1 invrel_{j,i,t-1} + \alpha_2 invrel_{j,i,t-1} \times X_{j,i,t-1} + \alpha_3 Z_{i,t-1} + u_{j,i,t}, \quad (8)$$

$$\Delta tpinvrel_{j,i,t} = \alpha_0 + \alpha_1 tpinvrel_{j,i,t-1} + \alpha_2 tpinvrel_{j,i,t-1} \times X_{j,i,t-1} + \alpha_3 Z_{i,t-1} + u_{j,i,t}, \quad (9)$$

where the dependent variables are defined as $\Delta invrel_{j,i,t} = invrel_{j,i,t} - invrel_{j,i,t-1}$ and $\Delta tpinvrel_{j,i,t} = tpinvrel_{j,t} - tpinvrel_{j,t-1}$. We interact $invrel_{j,i,t-1}$ and $tpinvrel_{j,i,t-1}$ with variables $X_{j,i,t-1}$ measuring potential distress period at time $t-1$. Specifically, $X_{j,i,t-1}$ include the following variables: $peak_{t-1}$ is a dummy variable equal to 1 if $t-1$ corresponds to the first and last hour of trading; $high_{j,i,t-1}$ in Equation (8) (respectively in Equation (9)) is a dummy variable equal to 1 when $invrel_{j,i,t-1}$ ($tpinvrel_{j,i,t-1}$ respectively) is 2 standard deviations greater than its mean; $volat\ high_{i,t-1}$ is a dummy variable equal to 1 when the standard deviation of 1 minute returns in stock i over the preceding 30 minutes interval $volatility_{i,t-1}$ is 2 standard deviations greater than its mean; $loss_{j,t-1}$ is a dummy variable equal to 1 when a trader's 30-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean). The stock specific control variables $Z_{i,t-1}$ include: $ret_{i,t-1}$ the return of stock i over the preceding 30 minutes interval; $oib_{i,t-1}$ buy minus sell trading volume in stock i, expressed as a ratio of total trading in stock i; $volatility_{i,t-1}$ standard deviation of 1 minute returns in stock i; $spread_{i,t-1}$ bid-ask spread estimated from the order book, expressed as a ratio of the mid-quote; $volume_{i,t-1}$ total trading volume. Each of the control variables are standardized at stock level. Standard errors are clustered by time. The estimation results are presented in Tables 2.

Insert Table 2 about here

As seen in Panel A of Table 2, the co-efficient associated with $invrel_{j,i,t-1}$ is consistently negative and statistically significant with a p-value less than a 1% level of significance – clear evidence of a mean reversion in relative ordinary inventories of VLPs. To provide some perspective on the economic significance of these coefficients, we should note that a mean reversion coefficient of -0.081 implies that VLP inventories have a half-life of approximately 4.10 hours, considerably smaller than the multi-day half-life of NYSE specialists (Madhavan and Smidt, 1993 and Hasbrouck and Sofianos, 1993) and LSE dealers (Hansch, Naik and Viswanathan, 1998 and Naik and Yadav, 2003a). Also, we find that controlling for prevailing market conditions – such as volatility, bid-ask spread and volume – does not affect the economic or statistical significance of the co-efficient of mean reversion in VLP inventories.

Consistent with the results of earlier tests of inventory models, we also find that the speed of correction is significantly greater when the deviation from the target inventory level is greater than 2 standard deviations. Further, we find that the speed of inventory mean reversion is significantly greater during the first and last hour of trading. This evidence is consistent with the argument that VLPs are more sensitive to inventory imbalances when informed traders are more likely to act on their private information, and when they approach their daily markers and deadlines (Anand, Chakravarty and Martell, 2005). Next, consistent with one of the key implications of the Ho and Stoll (1983) model, we find that inventory mean-reversion is also significantly greater when stock return volatility is two standard deviations greater than its mean. Finally, we find that inventory mean reversion significantly increases when a VLP suffer an abnormal loss - when (30-minute) aggregate revenue from all the 50 stocks in the sample is more than two standard deviations below its mean. This evidence is in line with the predictions of the Brunnermeier and Pedersen (2008) model that intermediaries are more likely to liquidate their inventories when their funding is constrained.

Next, we examine mean reversion in relative portfolio inventories. Panel B of Table 2 shows that, similar to the case of ordinary inventories, the co-efficient of mean reversion (associated with $tpinvrel_{j,i,t-1}$) is consistently negative and statistically significant. Furthermore, we also find that the portfolio inventories revert significantly faster when portfolio inventory imbalances are two standard deviations greater than their mean, during the first and last hour of the trading day, when stock price volatility is greater than two standard deviations greater than its mean, and when VLPs suffer an abnormal loss in their portfolio holdings. These results are perfectly in accordance with the theoretical predictions of Ho and Stoll (1983). That the speed of mean reversion in correlated portfolio inventories is significantly greater than that associated with ordinary inventories is central to our study. The unconditional coefficient of mean reversion is -0.11, which implies that the half-life of portfolio inventories is less than 3 hours – almost an hour sooner than the half-life of ordinary inventories. Also, the conditional rates of mean reversions are even more significantly faster than those of ordinary inventories. For example, the half-life of portfolio inventories when VLPs face abnormal losses is just over 1.5 hours, and the same for ordinary inventories is about 2.8 hours. These results strongly support the predictions of Hypothesis H1a.

Insert Figure 1 about here

A more direct comparison of speed of mean reversion in ordinary and correlated portfolio inventories is presented in Figure 1. Panel A presents a stock level comparison and Panel B presents the trader level comparison. As seen in Panel A, but for a few outliers, the rate of mean reversion in portfolio inventories is greater than the same for ordinary inventories. Off the 50 stocks we study, ordinary inventories revert faster than portfolio inventories only for two stocks. The trader level comparison, presented in Panel B, presents a similar story. The difference between the two rates of mean reversion is either insignificant or negative (portfolio inventories revert faster than ordinary inventories). The clear left-shift in the distribution of the difference between the two rates also shows that results obtained in the regression analyses are not driven by outliers.

It is also important to examine our results that VLPs manage correlated portfolio inventories rather than just stock-level inventories in context of the main predictions of Froot and Stein (1998). In their model, intermediaries base their decisions on the unhedgeable component of inventory risk. Since the NSE has an active index futures markets, most of portfolio inventory risk would be theoretically hedgeable.[11] Therefore, VLPs could employ index futures to manage the hedgeable (market) component of portfolio inventory risk, reducing the likelihood of observing significant mean reversion in portfolio inventories. However, given the high frequency with which VLPs trade, they would also be required to regularly change their index futures positions to ensure that portfolio inventory risk is hedged, making it a costly risk management strategy. In fact, our results are consistent with the argument that VLPs, trading at high frequencies, manage their portfolio inventory risk whilst operating in the equity markets itself, because the costs of high turnover in the index futures positions would render theoretically hedgeable risks practically unhedgeable.

Next, we examine the type of stocks and VLPs from whom portfolio inventory management matters more than ordinary inventory management. To do so we estimate the two regressions on the trader and on the stock level. The trader-level first regression is:

$$mean\ rev\ diff_j = \alpha_0 + \alpha_1 fin_j + \alpha_2 active_j + \alpha_3 aggressive_j + u_j, \qquad (10)$$

where the dependent variable $mean\ rev\ diff_j$ is difference between the rates of mean reversion in portfolio and ordinary inventories of the VLP j, (coefficients a_1 estimated from Equations (8) and (9)) aggregated at traders' level over the 50 stocks. We define $active_j$ as a dummy variable equal to 1 if the VLP is the one of the 10 most active (in terms of number of limit orders posted) VLPs; $aggresive_j$ is the ratio of an VLP's j daily aggressive trading volume (trades where the VLPs places the aggressive order) and daily total trading volume of the VLP j.

Finally, fin_j is a dummy variable equal to 1 if the VLP j is identified as a financial institutional trader in the dataset. We expect trading strategies of financial institutional traders to be most driven by speculative or informational reasons for the following reasons. One, a large body of literature shows that such institutional investors are the most informed and tend to improve the informational efficiency of securities they trade in.[12] Two, not only the general evidence, even evidence specific to the NSE is consistent with financial institutional investors (FIN) being the most informed traders. Kumar, Thirumalai and Yadav (2020) study a random selection of 100 stocks between January 2005 and June 2006 and find that FIN are significantly more informed than other traders on the NSE. Finally, we also find that orders placed by FIN are the most informed over different horizons.[13] Hence, to the extent FIN are most likely to trade for informational reasons rather than for purely market-making reasons, we expect to observe a lesser degree of mean reversion in their correlated portfolio inventories than in the correlated portfolio inventories of other VLPs.

[11] In unreported results, we find that the average pair-wise correlation in idiosyncratic returns is close to zero, indicating that the unhedgable component of portfolio inventory risk would be negligible.
[12] See, for example, Boehmer and Kelly (2009), Badrinath, Kale, and Noe (1995), and Chordia, Roll, and Subrahmanyam (2011).
[13] Evidence is available in Table B1 in Internet Appendix B.

The stock-level regression is as follows:

$$mean\ rev\ diff_i = \alpha_0 + \alpha_1 spread_i + \alpha_2 ret_i + \ \alpha_3 volatility_i + \alpha_4 volume_i + u_i, \quad (11)$$

where the dependent variable $mean\ rev\ diff_i$ is difference between the rates of mean reversion in portfolio and ordinary inventories of stock i (coefficients a_1 estimated from Equations (8) and (9)), aggregated at the stock level over 100 traders. The other control variables include: $spread_i$ defined as the time-series average of relative bid-ask spread of stock i estimated from the order book and expressed as a ratio of the mid-quote; ret_i defined as the time series average of 30 minutes stock returns $ret_{i,t}$; $volatility_i$ is the time series average of the standard deviation $volatility_{i,t}$ variable; $volume_i$ is the time series average of the 30 minutes trading volume $volume_{i,t}$. Although the limited cross-section of traders (100 traders) and stocks (50) naturally constrains a more detailed analysis, estimation results of models (10) and (11) provide an interesting characterization of mean reversion in VLPs' inventories.

Insert Table 3 about here

The estimation results of Equation (10) are presented in Panel A of Table 3 while Panel B contains the estimation results of Equation (11). There are two important results presented in Panel A. One, the intercept, indicating the average difference between portfolio and ordinary inventory mean reversion coefficients, is negative and statistically significant, evidence consistent with the results presented in Figure 1 and our Hypothesis H1a. Two, mean reversion in correlated portfolio inventories is significantly lower for FINs (p value < 0.05) relative to other VLPs; and it is significantly greater for the most passive of VLPs (p value < 0.05). The more likely a VLP is informed and trade based on information, and the less she is concerned about managing portfolio inventories rather than ordinary inventories. This supports our Hypothesis H1c. Results presented in Panel B again show a negative and significant intercept – on average, portfolio inventories mean revert faster than ordinary inventories. More importantly, we also find that correlated portfolio inventories are especially more important for illiquid stocks. This evidence is consistent with the argument that since VLPs focus on portfolio inventories rather than ordinary inventories, they manage their (portfolio) inventory imbalances through trades in liquid stocks rather than illiquid stocks.

In sum, we find that not only do correlated portfolio inventories mean revert at a statistically and economically significant rate, they do so significantly faster than ordinary inventories. Moreover, we find that portfolio inventory imbalances matter more than ordinary inventory imbalances especially when imbalances are two standard deviations greater than their mean, during the first and last hour of the trading day, when stock price volatility is greater than two standard deviations greater than its mean, when VLPs suffer an abnormal loss in their portfolio holdings, for illiquid stocks, and for VLPs most likely to trade for informational reasons.

4.3. Order placement and trader inventories

In this section, we test our Hypothesis H1b regarding the relation between order placement behaviour of VLPs and their stock and portfolio relative inventories. In our first test, we consider three states of order placements. One, the VLP has limit orders only on the buy-side of the book (denoted as *"Buy Orders Only"*). Two, the VLP has limit orders only on the sell-side of the book (denoted as *"Sell Orders Only"*). Three, the VLP is indifferent between the two sides of the limit order book, wherein the VLP either places orders on both sides of the book or is absent from both (denoted as *"Sell and Buy or NoOrders"*). Next, we empirically examine the effect of stock and portfolio (relative) inventories on the probability of the VLP being in one of the three aforementioned states of order placement. According to Ho and Stoll (1983), the probability of a VLP being in the second (first) order placement state should increase (decreases) with an increase in portfolio (relative) inventories.

We test this by estimating the following multinomial logit regression with the aforementioned three quoting regimes:

$$P(\text{"}Buy\ Orders\ Only\text{"}) = \frac{exp(\alpha_{ob}+\alpha_b^T X_{j,i,t-1})}{1+exp(\alpha_{ob}+\alpha_b^T X_{j,i,t-1})+exp(\alpha_{os}+\alpha_s^T X_{j,i,t-1})},$$

$$P(\text{"}Sell\ Orders\ Only\text{"}) = \frac{exp(\alpha_{os}+\alpha_s^T X_{j,i,t-1})}{1+exp(\alpha_{ob}+\alpha_b^T X_{j,i,t-1})+exp(\alpha_{os}+\alpha_s^T X_{j,i,t-1})},$$

$$P(\text{"}Buy\ and\ Sell\ or\ NoOrders\text{"}) = \frac{1}{1+exp(\alpha_{ob}+\alpha_b^T X_{j,i,t-1})+exp(\alpha_{os}+\alpha_s^T X_{j,i,t-1})}, \quad (12)$$

where the set of control variables $X_{j,i,t-1}$ include $invrel_{j,i,t-1}$; $pinvrel_{j,i,t-1}$; stock return $ret_{i,t-1}$; $oib_{i,t-1}$ buy minus sell trading volume, expressed as a ratio of total trading; $volume_{i,t-1}$ stock i trading volume, the interaction variable $pinvrel_{j,i,t-1} \times fin_j$, and the dummy variable fin_j. Regime *"Sell and Buy or NoOrders"* is taken as reference category.

Insert Table 4 about here

The estimation results are presented in Panel A of Table 4. It is not only the inventories in the concerned stock but inventories in the rest of the portfolio that also significantly affect order placement behaviour. Specifically, coefficient associated with $invrel_{j,i,t-1}$ is consistently positive and significant for the "*Sell Order Only*" regime; and negative and significant for the "*Buy Orders Only*" regime. A one-standard deviation increase in stock-level relative inventories increases the odds of a VLP submitting only sell orders by 10.3% and reduces the odds of submitting only buy order by 3.4%. The effect of inventories in the rest of the portfolio is captured $pinvrel_{j,i,t-1}$. The results indicate that portfolio inventory imbalances incrementally effect order placement strategy of a VLP – a one-standard deviation increase in $pinvrel_{j,i,t-1}$ increases the odds of a VLP submitting only sell orders by 5.2%. This supports our hypothesis H1b.

Further, adding other market variables, such as stock return and order imbalances, does not dilute the effect of stock and portfolio inventory on order placement behaviour of voluntary liquidity providers. Also, consistent with the argument that these VLPs function as de-facto market makers in this market, we find that their probability of submitting only sell orders increases with increases in stock returns and aggregate order imbalances.

Finally, the interaction term $pinvrel_{j,i,t-1} \times fin_j$ is positive and significant for "*Buy Orders Only*". This lends support to Hypothesis H1d. FINs, who are more likely to trade on information, tend to be less influenced by portfolio inventory imbalanes than the other VLPs.

We next examine the effect of stock and portfolio inventories on the probability of a VLP switching between a "*Buy Orders Only*" and a "*Sell Orders Only*" regime. The analysis here is similar to the aforementioned analysis, except that we have dropped the regime where VLPs are indifferent between placing buy and sell orders. As seen in Panel B of Table 4, while the results relating to stock inventory are similar to the ones presented in Panel A, the results relating to the incremental effect of portfolio inventory are even stronger than the ones previously discussed. A one-standard deviation increase in $pinvrel_{j,i,t-1}$ increases the odds of a VLP changing from a "*Buy Order Only*" regime to a "*Sell Orders Only*" regime by 6.60%. Again, controlling for other market conditions that could affect order placement regimes does not alter our portfolio inventory result.

Having examined the effect of stock and correlated portfolio inventory on order placement strategy using discrete models, we now extend the analysis to a continuous setting and examine the relation between VLP order imbalances and inventories. Specifically, we test for the effect of inventory variables on $trader\ oib_{j,i,t}$ – a VLP's order imbalance (buy minus sell trader j's total order volume, expressed as a ratio of the trader j's total order volume) in a given stock during a given 30-minute time interval; it is standardized by trader and stock. Specifically, we estimate the following regression:

$$trader\ oib_{j,i,t} = \alpha_0 + \alpha_1 invrel_{j,i,t-1} + \alpha_2 pinvrel_{j,i,t-1} + \alpha_3 X_{j,i,t-1} + u_{j,i,t}, \quad (13)$$

where the set of control variables $X_{j,i,t-1}$ contains lagged dependent variable $trader\ oib_{j,i,t-1}$; stock return $ret_{i,t-1}$, stock-level trading order imbalance $oib_{i,t-1}$, standard deviation of 1 minute returns $volatility_{i,t-1}$; trading volume $volume_{i,t-1}$. We also interact $pinvrel_{j,i,t-1}$ variable with FIN_j to test for the effect of information on portfolio inventory management. Each of the control variables are standardized at stock level. Standard errors are clustered by time.

Insert Table 5 about here

As shown in Table 5, the inventory variables are consistently negative, and statistically and economically highly significant. Specifically, we find that a one-standard deviation increase in stock inventory reduces VLPs' order imbalance by 0.046 standard deviations. More importantly, we find that even after controlling for stock inventory, VLPs' inventories in correlated securities affect VLP order imbalance significantly. A one-standard deviation increase in $pinvrel_{j,i,t-1}$ reduces order imbalance by 0.02 standard deviations. That trader order imbalances in a stock are incrementally affected by inventories in other stocks that make-up her portfolio is consistent with our previous results and our central hypothesis that VLPs manage correlated portfolio inventory, not ordinary inventory. Also, similar to the previously discussed results, the effect of correlated portfolio inventory is impervious to other market factors (such as stock return, lagged VLP order imbalance and market-wide order imbalance) that could affect VLP order imbalances. Furthermore, in line with Hypothesis H1d, the effect is weaker for FINs, who are least likely to be pure market-makers.

4.4. Market liquidity, pricing errors and trader inventories

In this section we examine the relationships between VLP stock and portfolio inventories and measures of market quality, such as market liquidity and price pressures. In order to test our hypotheses H2a and H2b we examine the effect of both the magnitude and the dispersion of VLP stock and portfolio inventories on different dimensions of market quality. While previous analyses focus on trader-level inventories, here we consider characteristics of aggregate inventory.

We start our analysis by looking at the effect of dispersion and the magnitude of inventories on the bid-ask spreads. We estimate the following two regression models:

$$spread_{i,t} = \alpha_0 + \alpha_1 invrange_{i,t-1} + \alpha_2 pinvrange_{i,t-1} + \alpha_3 X_{i,t-1} + u_{i,t}, \quad (13)$$

$$spread_{i,t} = \alpha_0 + \alpha_1 \left|invav_{i,t-1}\right| + \alpha_2 \left|pinvav_{i,t-1}\right| + \alpha_3 X_{i,t-1} + u_{i,t}. \quad (14)$$

In model (13), $invrange_{i,t}$ denotes our measure of inventory dispersion, defined as the interquartile range of stock-level inventory ($inv_{i,t}$) in a given time period across VLPs, $pinvrange_{i,t}$ is the interquartile range of portfolio inventory ($pinv_{i,t}$) in a given time period across VLPs. In model (14) $\left|invav_{i,t}\right|$, the absolute value of the average stock-level inventory of VLPs in a given time period, is our measure of net capital invested by the VLPs in a given stock. Similarly, $\left|pinvav_{i,t}\right|$ measures the net capital invested in the rest of the portfolios held by the VLPs. Control variables include $volatility_{i,t-1}$ defined as the standard deviation of 1 minute returns; trading volume $volume_{i,t-1}$; $open\ close_{t-1}$ is a dummy variable equal to 1 during first and last hour of trading. $pspread_{i,t}$ is the equal weighted average bid-ask spread of the rest of the 49 stocks in the Nifty index. Finally, liquidity in stock is also a function of adverse selection and information spillover from correlated securities, but controlling for such an information effect is not straight forward. However, our data also provides information on trader categories; we exploit this feature to measure informed trading. Kotha, Thirumalai and Yadav (2020) show that financial institutions are the most informed traders on the NSE. Accordingly, we proxy for the quantum of informed trading by absolute value of order imbalances and portfolio order imbalances of financial institutions $\left|oibfin_{i,t-1}\right|$ and $\left|poibfin_{i,t-1}\right|$ respectively. All of the variables except $open\ close_{t-1}$ are standardized by stock.

Insert Table 6 about here

The results of the analysis are presented in Table 6. The negative relation between bid-ask spreads and dispersion of portfolio inventories is statistically and economically significant. A one-standard deviation increase in $pinvrange_{i,t-1}$ is associated with a reduction in next-period bid-ask spreads by 0.22 standard deviations. Also, controlling for the liquidity spillovers and information effects from other stocks (Cespa and Foucault, 2014), along with other pertinent variables such as stock volatility and volume, does not qualitatively change the relation; in the full specification, a one-standard deviation increase in $pinvrange_{i,t-1}$ reduces bid-ask spreads by 0.10 standard deviations. Surprisingly, the relation between $invrange_{i,t-1}$ and bid-ask spreads is statistically insignificant. This insignificant relation between stock-level inventory dispersion and bid-ask spreads is consistent with the findings reported in Manaster and Mann (1996). Further, as shown in the table, bid-ask spreads are significantly wider following large (magnitude) aggregate portfolio inventories. A one-standard deviation increase in $|pinvav_{i,t-1}|$ is associated with an increase in next-period bid-ask spreads by 0.21 standard deviations and by 0.05 standard deviations in the full specification. Again, we find no significant relation between stock-level aggregate inventory and bid-ask spreads.

We turn now to examining the relation between average inventory of VLPs and the difference in the depth of the buy-side and the sell-side of the limit order book. According to inventory models, an increase in average VLP inventories (i.e., when VLPs have accumulated inventory in a stock) would result in greater depth on the sell-side of the order book than the buy-side – greater the average VLP inventory, the more negative the difference between buy-side and sell-side depth. In accordance with the focus of this paper, we examine the effect of not only stock inventory but also correlated portfolio inventory on the difference in the depth of the buy-side and the sell-side of the limit order book.

To test this, we estimate the following two regression models:

$$diff\ depth_{i,t} = \alpha_0 + \alpha_1 invav_{i,t-1} + \alpha_2 pinvav_{i,t-1} + \alpha_3 X_{i,t-1} + u_{i,t}, \quad (15)$$

where $diff\ depth_{i,t} = 2(buy\ depth_{i,t} - sell\ depth_{i,t})/(buy\ depth_{i,t} + sell\ depth_{i,t})$ and $buy\ depth_{i,t}$ and $sell\ depth_{i,t}$ are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. The dependent variable is standardized by each stock. Control variables $X_{i,t-1}$ include the lagged stock return $ret_{i,t-1}$; order imbalance $oib_{i,t-1}$; the market aggregate difference in depth $diff\ pdepth_{i,t}$ defined as equal weighted average in $diff\ depth_{i,t}$ over the rest of the 49 stocks in the Nifty index; absolute value of portfolio order imbalances of financial institutions $|poibfin_{i,t-1}|$.

Insert Table 7 about here

The results are presented in Table 7. The portfolio inventory is consistently negatively related to $diff\ depth_{i,t}$ – the relation is statistically and economically significant as well. A one-standard deviation increase in $pinvav_{i,t-1}$ is associated with a reduction in $diff\ depth_{i,t}$ by 0.13 standard deviations. Further, similar to previous results, controlling for the liquidity spillovers and information effects from other stocks in the Nifty index and other pertinent variables, such as stock volatility and volume, does not qualitatively change the results. In the full specification, a one-standard deviation increase in $einvav_{i,t-1}$ is associated with a reduction in $diff\ depth_{i,t}$ by 0.05 standard deviations. Similarly, stock inventory is also negatively related to $diff\ depth_{i,t}$. A one-standard deviation increase in $invav_{i,t-1}$ is associated with a reduction in $diff\ depth_{i,t}$ by 0.14 standard deviation and by 0.12

standard deviation in the full specification. That VLP stock and portfolio inventories significantly affect the relative buy and sell side depths is consistent with the predictions of Ho and Stoll (1983). [14]

Our final tests of hypotheses H2a and H2b concern the relation between both the dispersion of and the magnitude of stock and correlated portfolio inventories and pricing errors created from price pressures sustained by the intermediaries. We start by identifying the price pressure effect of stock and portfolio inventories using a state space approach, similar to the one employed in Hendershott and Menkveld (2014).

We model the observed log price series ($p_{i,t}$) as the sum of a nonstationary efficient price series ($m_{i,t}$) and a stationary pricing error ($s_{i,t}$), which captures the transitory price effects. Specifically, the observation equation of our model for stock i and time t is

$$p_{i,t} = m_{i,t} + s_{i,t}. \tag{16}$$

The efficient price series follows a random walk with a drift

$$m_{i,t} = m_{i,t-1} + \beta_{im} r_t^M + w_{i,t,} \tag{17}$$

where r_t^M is the demeaned market return, $w_{i,t}$ is the idiosyncratic innovation assumed to be a normally distributed white noise process. The process for the stationary pricing error has the following form:

$$s_{i,t} = \alpha_i invav_{i,t} + \delta_i pinvav_{i,t} + \beta_{is} ret_t^M + u_{i,t}, \tag{18}$$

where the error term $u_{i,t}$ is normally distributed and uncorrelated with $w_{i,t}$. The ret_t^M term captures the adjustment to common factor innovation.

In order to estimate the effect of inventory dispersion across different traders, we estimate the following extended version of the pricing error equation:

$$s_{i,t} = \alpha_{0i} invav_{i,t} + \alpha_{1i} invav_{i,t} \times invrange_{i,t} + \delta_{0i} pinvav_{i,t}$$
$$+\delta_{1i} pinvav_{i,t} \times pinvrange_{i,t} + \beta_{is} ret_t^M + u_{i,t}. \tag{19}$$

In order to capture non-linearity of the dispersion on pricing errors, we also consider alternative measure of the inventories dispersion. Specifically, we use the squared inter-quartile range as well as the dummy variable $dinv_{i,t}$ that is equal to 1 if the inventory inter-quartile range $invrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. Similarly, $dpinv_{i,t}$ is equal to 1 if the inventory inter-quartile range $pinvrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise.

We perform our empirical analysis on a stock-by-stock level. For each stock we estimate the model using maximum likelihood method, in which the error terms $w_{i,t,}$ and $u_{i,t}$ are assumed to be normally distributed. Table 8 reports average of estimates of the state space model across all stocks.

Insert Table 8 about here

We find a significant price pressure effect of portfolio inventory. The coefficient δ_i that measures the marginal price pressure stemming from portfolio inventory series is negative and

[14] We also examine the effect of correlated portfolio inventory on the difference in the slope of the buy-side and the sell-side of the limit order book. We reach similar conclusions as in the case of depth variable. The results are available in Table A9 in Internet Appendix A.

statistically significant. This suggests that prices are temporarily low when liquidity providers' position in other stocks is above long-term average, and temporarily high when they hold positions in other stocks below long-term average level. This effect exists even after controlling for the price pressure coming from ordinary inventory of stock i. The negative and significant estimates of parameter α_i, measuring the marginal price pressure of ordinary inventory, is consistent with the results documented in Hendershott and Menkveld (2014).

The economic effect of correlated portfolio inventory on pricing errors is sizable. A one standard deviation change in portfolio inventory creates a price pressure of -5.40 basis points, which is almost double the average bid-ask spread (Table 1, Panel A). The marginal effect of ordinary inventory on pricing errors is about five times larger than that of portfolio inventory.

Dispersion of inventories across traders also matters for the magnitude of pricing errors, as suggested by our hypothesis H2b. When the interaction coefficients are included in the specification, the marginal effect of inventory on pricing errors during times of low inventory dispersion increases in magnitude and equals -14.82 basis points. Further, consistent with H2b, we find that the effect of correlated portfolio inventory on price pressures significantly decreases when portfolio inventory dispersion is large (dispersion squared), and that the price pressure effect of portfolio inventory dissipates when its dispersion is greater than 1 standard deviation. The dispersion of inventory also changes the marginal effect of ordinary inventory on pricing errors but the effect is more modest.

4.5. Stressful episodes and trader inventories

In this section, we examine how the magnitudes of stock and portfolio inventories, and their dispersions, are related to the probability and number of stressful periods.

We identify stressful episodes using two methods. One, similar to Brogaard et al. (2018), we identify the extreme price movements (EPMs) that belong to the 99.9th percentile of 1-second absolute mid-quote returns for each stock. For this we denote a dummy variable $extreme_{i,t}$ that equals 1 if stock i at time t experience at least one extreme price movement and the variable $nrextreme_{i,t}$ that denotes the number of extreme price movements in the corresponding 30 minutes interval.

Two, we use the Lee and Mykland (2008) methodology to identify jumps in stock returns. To identify transient jumps, we first aggregate data into one-minute mid-quote returns indexed by τ. For each minute τ we estimate the instantaneous volatility of a particular stock return based on the realized bi-power variation using the window of the previous K observations given by:

$$\sigma_\tau^2 = \frac{1}{K-2} \sum_{s=\tau-K+2}^{\tau-1} |r_s|\,|r_{s-1}|, \tag{20}$$

where r_τ denoted log one-minute return at time τ (we drop index i for ease of notation). We then take the following ratio of this estimated volatility to the next realized return in order to determine whether there was a jump arrived at τ and its magnitude:

$$L_\tau = \frac{r_\tau}{\sigma_\tau} \tag{21}$$

Lee and Mykland (2008) derive that the critical values at 1% confidence to reject the null hypothesis of no jumps are determined by the inequality $\frac{|L_\tau|-C_n}{S_n} > 4.6001$, where $C_n = \frac{(2\log n)^{1/2}}{c} - \frac{\log\pi+\log(\log n)}{2c(2\log n)^{1/2}}$, $S_n = \frac{1}{c(2\log n)^{1/2}}$, $c = \sqrt{2}/\sqrt{\pi} \approx 0.7979$ and $n = 25{,}740$ is the number of observations in the sample (accounting for the number of one minutes interval within the 3 month period based on 6.5 hours trading day). We choose window size $K = 160$.

Each jump that is detected using this procedure is further classified as transient and permanent. A jump at time τ_0 is classified as transient if and only if there exits $\tau \in (\tau_0 + 1, \tau_0 + J)$ such that:

$$p_{\tau_0-1} - p_\tau \leq 0, \text{ when } L_\tau > 0 \text{ and } p_{\tau_0-1} - p_\tau \geq 0, \text{ when } L_\tau < 0. \quad (22)$$

In other words, if the price p_τ reverts back to its pre-jump level within J minutes. Empirically, this can correspond to price reversals due to overreaction after news arrival. For this exercise we use $J = 60$ seconds but the results are robust for larger values of J.[15]

Similar to the case of extreme price movements, we define a dummy variable $jump_{i,t}$ that equals 1 if stock i at time t experiences at least one transient price jump; and the variable $nrjumps_{i,t}$ that denotes the number of transient jumps in the corresponding 30 minutes interval.

Insert Figure 2 about here

Figure 2 plots the aggregate number of daily EPMs (Panel A) and the aggregate daily number of transient jumps (Panel B). The daily number of EPMs are close to zero for most days in the data. However, we observe a dramatic spike in the number of EPMs on May 22, 2006. That this day also happens to be one of the biggest crashes in the history of the Indian stock market adds more credence to our identification of stressful episodes.[16] The general trends in the daily number of jumps are similar to the trend in the daily number of EPMs. The only notable exception is on April 5, where many stocks exhibit price movements of moderate magnitude. However, since these price movements are significant relative to the volatility of the stock returns, they are identified as jumps. Also, similar to the number of EPMs, the number of jumps spike around the May 22, 2006. Getmansky et al.(2018), who employ a data similar to ours for one representative stock on the National Stock Exchange, also identify jumps on the 19th and 22 of May, 2006.

We estimate the following Logit regressions to examine the relation between the inventory of intermediaries and the likelihood of stressful episodes occurring in a thirty-minute interval in stock:

$$P(stress_{i,t} = 1) = \frac{exp(\alpha_o + \alpha_1^T X_{i,t-1})}{1 + exp(\alpha_o + \alpha_1^T X_{i,t-1})},$$

[15] For robustness we also consider a case of partial price reversals, where a jump at time τ_0 is classified as transient if it reverts back during a pre-specified window J to a level that is within 1.65 standard deviations from the pre-jump price p_{τ_0-1}. The intuition is to check if the price reverts back to within the 10% confidence interval bounds that are determined under the null (pure diffusion model). More formally, a jump that occurs at time τ_0 is called transient if and only if there exits $\tau \in (\tau_0 + 1, \tau_0 + J)$ such that $|p_{\tau_0-1} - p_\tau| < 1.65\sigma_\tau\sqrt{\tau - \tau_0}$.

[16] https://www.rediff.com/money/2006/may/18spec.htm

$$P\left(stress_{i,t}=0\right)=\frac{1}{1+exp(\alpha_o+\alpha_1^T X_{i,t-1})}, \quad (23)$$

where the variable $stress_{i,t}$ stands for the dummy variable equal to 1 if the stock i experienced a stressful episode at time t measured by either extreme price movements $\left(stress_{i,t} \equiv extreme_{i,t}\right)$ or by transient jumps $\left(stress_{i,t} \equiv jump_{i,t}\right)$. The set of independent variables $X_{i,t-1}$ includes the following: $invrange_{i,t-1}$ is the interquartile range of trader $inv_{j,i,t}$ at time t; $pinvrange_{i,t-1}$ is the interquartile range of trader $pinv_{j,i,t}$ at time t; $\left|invav_{i,t-1}\right|$ is the absolute value of traders' average stock inventory $inv_{j,i,t}$; $\left|pinvav_{i,t-1}\right|$ is the absolute value of traders' average stock inventory $pinv_{j,i,t}$; $volatility_{i,t-1}$ denotes the standard deviation of 1 minute returns of stock i over the corresponding 30 minutes interval; $volume_{i,t-1}$ is the trading volume; $\left|oib_{i,t-1}\right|$ is the absolute value of order imbalance in stock i; $\left|poibfin_{i,t-1}\right|$ is the absolute value of order imbalance of financial institutions in stock i; $open\ close_{t-1}$ is a dummy variable equal to 1 during first and last hour of trading; lagged dependent variable $stress_{i,t-1}$. All continuous variables are standardized by stock.

In addition to this we also estimate the Tobit regression, where the dependent variable is the number of stressful events (either $nrextreme_{i,t}$ or $nrjump_{i,t}$) and the independent variables are as in Equation (23).

Insert Table 9 about here

Panel A of Table 9 presents the results of the analyses where we proxy stressful episodes by EPMs. The likelihood of an EPM is significantly and negatively related to the dispersion of portfolio inventories. A one-standard deviation increase in $pinvrange_{i,t-1}$ is associated with a reduction in the odds of observing an EPM episode in the next period by 74.46%. Similarly, as seen in the results from Tobit regressions, the number of EPMs are also significantly and negatively related to dispersion of portfolio inventories – one-standard deviation increase in $pinvrange_{i,t-1}$ is associated with a reduction in the number of EPMs in the next period by 1.59 units. Similarly, consistent with the models of inventory management, a one-standard deviation increase in the dispersion of stock-level inventories is associated with a reduction in the odds of observing an EPM episode in the next period by 62.30% and the number of EPM episodes by approximately 1.01 units.

Next, we also find that the magnitude of aggregate correlated portfolio inventories is significantly and positively related to the likelihood and the number of EPMs. A one-standard deviation increase in $\left|pinvav_{i,t-1}\right|$ is associated with an increase in the odds of observing an EPM episode in the next period by 14 times and the number of EPMs by (approximately) by 3 units. However, the relation between the magnitude of stock-level inventories and the number of EPMs and the likelihood of EPMs is negative and only marginally statistically significant.

Panel B of Table 9 presents the results of the analyses where we proxy stressful episodes by transient jumps. The likelihood of a transient jump is also negatively and significantly related to the dispersion of correlated portfolio inventories – a one-standard deviation increase in $pinvrange_{i,t-1}$ is associated with an decrease in the odds of observing an EPM episode in the next period by 77.88%. Similarly, as seen in the results from Tobit regressions, the number of transient jumps are also significantly and negatively related to the dispersion of portfolio inventories - one-standard deviation increase in $pinvrange_{i,t-1}$ is associated with a decrease in the number of EPMs in the next period by 1.95 units. Similarly, a one-standard deviation increase in the dispersion of stock-level inventories decreases the odds of observing a transient jump by 51.51% and the number of transient jumps by approximately 0.91 units.

The magnitude of aggregate portfolio inventories is positively and significantly related to the likelihood and the number of transient jumps. A one-standard deviation increase in $|pinvav_{i,t-1}|$ is associated with an increase in the odds of observing an EPM episode in the next period by 44.60% and the number of EPMs by 0.58 units. The relation between the magnitude of stock-level inventories and the number of jumps and the likelihood of jumps is statistically insignificant.

One potential concern that one may have is that our results are driven by reverse causality, which arises when extreme price movements or transient jumps trigger traders to rebalance their portfolio and reduce portfolio inventories. To mitigate this concern and control for potential reverse causality we estimate a VAR(p) model with six variables:

$$y_{i,t} = A_0 + A_1 y_{i,t-1} + \cdots + A_p y_{i,t-p} + u_{i,t},$$

where the verctor y_t takes one of the following specification for EPMs

$$y_{i,t} = \left[\Delta nrextreme_{i,t}, invrange_{i,t}, pinvrange_{i,t}, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|\right]^T, \quad (24)$$

$$y_{i,t} = \left[\Delta nrextreme_{i,t}, |invav_{i,t}|, |pinvav_{i,t}|, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|\right]^T, (25)$$

and one of the following specifications for transient jumps:

$$y_{i,t} = \left[\Delta nrjumps_{i,t}, invrange_{i,t}, pinvrange_{i,t}, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|\right]^T, \quad (26)$$

$$y_{i,t} = \left[\Delta nrjumps_{i,t}, |invav_{i,t}|, |pinvav_{i,t}|, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|\right]^T. \quad (27)$$

We choose the optimal lag value p based on AIC criterion. The VAR(p) model is estimated on the stock-by-stock level. Figure 3 present averages across all stocks of cumulative impulse responses of $\Delta nrextreme_{i,t}$ (see Panel A) and $\Delta nrjumps_{i,t}$ (see Panel B) variables to shocks in $pinvrange_{i,t}$ and $|pinvav_{i,t}|$.

Insert Figure 3 about here

The results supports our previous findings that an increase in $pinvrange_{i,t}$ is accosiated with a reduction of the average number of future extreme events while an increase in $|pinvav_{i,t}|$ is associated with an increase it. The cumulative impuslse responses of $\Delta nrextreme_{i,t}$ to both $pinvrange_{i,t}$ and $|pinvav_{i,t}|$ are statistically significant for up to 6 periods (about 3 hours) while the cumulative impuslse responses of $\Delta nrjumps_{i,t}$ are statistically significant beyond 10 periods.

5. Robustness Checks

In this section we perform a series of robustness checks to ensure that the main conclusions are not driven by specific choice of inventory aggregation, sampling frequency, and the number of voluntary liquidity providers identified as liquidity providers.

5.1. Equally-Weighted Portfolio inventory

Ho and Stoll (1983) define equivalent (portfolio) inventory, for each stock i, as the aggregate inventory of stocks in the portfolio weighted by the corresponding "betas" of each of those stocks with respect to stock i. However, betas estimated using intraday returns could be susceptible to measurement errors. To show that our results are not driven by these measurement errors, we replicate all of our results by using the equally-weighted inventory variable (assume beta is equal one for all stock pairs) instead of beta-weighted portfolio inventory (equivalent inventory) and demonstrate that the results hold regardless of the weighting employed.

We construct equally-weighted portfolio inventory series, $EWQ_{j,i,t}$ and $TEWQ_{j,t}$, for each trader j as follows:

$$TEWQ_{j,i,t} = Q_{j,i,t} + \sum_{k=1,k\neq i}^{k=50} Q_{j,k,t}, \tag{28}$$

$$EWQ_{j,i,t} = \sum_{k=1,k\neq i}^{k=50} EWQ_{j,k,t}. \tag{29}$$

$$EWpinv_{j,i,t} = \frac{EWQ_{j,t} - \overline{EWQ}_j}{stdev(EWQ_j)}, \tag{30}$$

$$TEWpinv_{j,i,t} = \frac{TEWQ_{j,i,t} - \overline{TEWQ}_{j,i}}{stdev(TEWQ_{j,i})}. \tag{31}$$

Finally, we employ relative inventories, which are calculated as a trader's standardized inventory minus the median standardized inventory across the VLPs in a stock, in our analyses:

$$EWprelinv_{j,i,t} = EWpinv_{j,i,t} - median(EWpinv_{i,t}^{LOTs}), \tag{32}$$

where $median(EWpinv_{i,t}^{LOTs})$ is the median standardized equally-weighted portfolio inventory across the VLPs in stock i at time t.

The results corresponding to Figure 1 and Tables 3 – 9 are available in Figure A1 and Tables A1 – A8 in Internet Appendix A. The results remain qualitatively the same.

5.2. Sampling frequency

Our analysis is conducted at a sampling frequency of 30 minutes. The sampling frequency choice is somewhat arbitrary. To mitigate this concern, we re-estimate the mean-reversion equations using 15 minutes and 60 minutes sampling frequencies. The results are available in Tables B2 and B3 in Internet Appendix B. The results are similar both qualitatively and quantitively. For example, portfolio inventories mean-revert faster than stock-level inventories, and the half-life of inventories remain quantitively similar over different sampling frequencies.

5.3.Number of liquidity providers

Although the VLPs we study, the most active 100, account for almost 45% of the volume of all limit orders submitted, there could be concerns that our results are driven by our choice of the number of traders. We address this concern by showing that liquidity providers continue to manage portfolio inventories rather than just stock-level inventories and that portfolio inventories imbalances influence trader behaviour and market quality even when we increase the number of VLPs from the most active 100 to the most active 150 and the most active 300. The most active 150 and 300 VLPs account for 48% and 55% of the submitted limit orders volume, respectively. The results, available in Tables B4-B19 in Internet Appendix B, remain qualitatively the same.

6. Conclusions

We investigate inventory risk management of voluntary liquidity providers (VLPs) in limit order book markets. VLPs are the *de-facto* 'market-makers' in LOB markets, emerging endogenously – and usually voluntarily – as a for-profit business that is, in aggregate, a net liquidity provider, trading on its own account with incoming buy and sell orders, bearing the cost and the risk of carrying unbalanced inventory exposures, and earning the premium for doing so. We specifically focus on how their trading, liquidity provision, and overall market quality in one security are influenced by their inventory risk exposure to other correlated securities in their portfolios. We use proprietary data with coded identities of these VLPs. Our data is from the *National Stock Exchange of India*, an equity market with among the highest number of daily trades globally.

Our results are in sharp contrast to the results of Naik and Yadav (2003a), who are able to analyse only the *centralized* firm-level inventories of the approximately 15 large market-making firms that serviced the London Stock Exchange at the time, firms that were *affirmatively obliged* to make a market, and during a time-period when public trading was entirely through telephones. Our data actually identifies individual trading accounts or trading units acting as VLPs; these LOB market VLPs also have no constraints in their trading arising from any affirmative obligations; and these VLPs are able to instantly trade electronically rather than go through telephones. Hence, we can cleanly test the predictions of Ho and Stoll (1983) for the trading of liquidity providers, and we find strong support for Ho and Stoll (1983). We find that liquidity providers actively manage not just their stock-level ordinary inventories, but also their portfolio inventories that include the correlated risk exposures arising from the other stocks in the liquidity provider's portfolio.

Our results also show that liquidity providers' inventories, including specifically correlated portfolio inventories, are a significant determinant of market quality. We find that market liquidity worsens when correlated portfolio inventories are large in magnitude, or less dispersed across different VLPs. We also find that these correlated portfolio inventories are a significant source of price pressures. Once again, this effect is particularly high during times of low dispersion of these correlated portfolio inventories across different VLPs.

Our results are consistent with liquidity providers' portfolio inventory management acting as an alternative channel for liquidity spillovers: a stock-specific liquidity demand shock in a security would affect liquidity providers' inventory (magnitude and/or dispersion) in the security, which would in turn impair liquidity providers' ability to provide liquidity in other stocks in their portfolio, leading to a drop in liquidity in those stocks as well.

Finally, we show that liquidity providers' portfolio inventory management is also potentially a source of market fragility. The likelihood and the number of extreme volatility episodes significantly increase with the magnitude of aggregate correlated portfolio inventories, and decrease with the dispersion of these correlated portfolio inventories across different VLPs.

Overall, our results demonstrate that liquidity providers' portfolio-based inventory risk management – that includes the effects of correlated risk exposures in other stocks in the portfolio – is not only a highly significant determinant of their trading behaviour and liquidiy provision activity, it is also an important source of market frictions and market fragility in limit order book markets. Inventory shocks from one security can propagate via this mechanism and significantly affect overall market liquidity, and the transitory volatility in other correlated stocks. Our results are relevant for all limit order book markets where liquidity is voluntarily provided by limit order traders simultaneously managing a cross-section of securities.

Our choice of sample period has been governed by the availability of proprietary data that included the coded identity of each VLP; and, as in Anand and Venkataraman (2016), corresponds to a period during which there was no algorithmic trading on the stock exchange. Therefore, our results cannot be driven by HFTs or algorithmic trading. Even without HFTs or algorithmic trading, we find that portfolio inventory management of VLPs can significantly drive market fragility, thereby highlighting the inherent fragility of LOB markets with voluntary liquidity suppliers. Furthermore, algorithmic traders have minimal attention costs and can implement trading strategies involving multiple securities considerably more quickly and easily. We believe that each of our results – our strong support for Ho and Stoll (1983), and strong evidence that portfolio-based cross-security inventory management of liquidity providers adversely impacts market quality, amplifies price pressures and extreme price movements, and increases overall liquidity fragility – should arguably be even stronger in the presence of computerized decision-making and trade execution. We leave examination of these and similar algorithmic trading related issues for future research.

Through providing another channel through which liquidity providers in LOB markets influence overall market quality, generate liquidity spillovers, and contribute to liquidity fragility, this paper has significant policy relevance in informing exchange and regulatory perspectives on affirmative obligations and designated market-making. We contribute to academic and regulatory understanding in this context by investigating a VLP's management of correlated exposures across different securities, just as Anand and Venkataraman (2016) do by investigating correlated trading of different VLPs.

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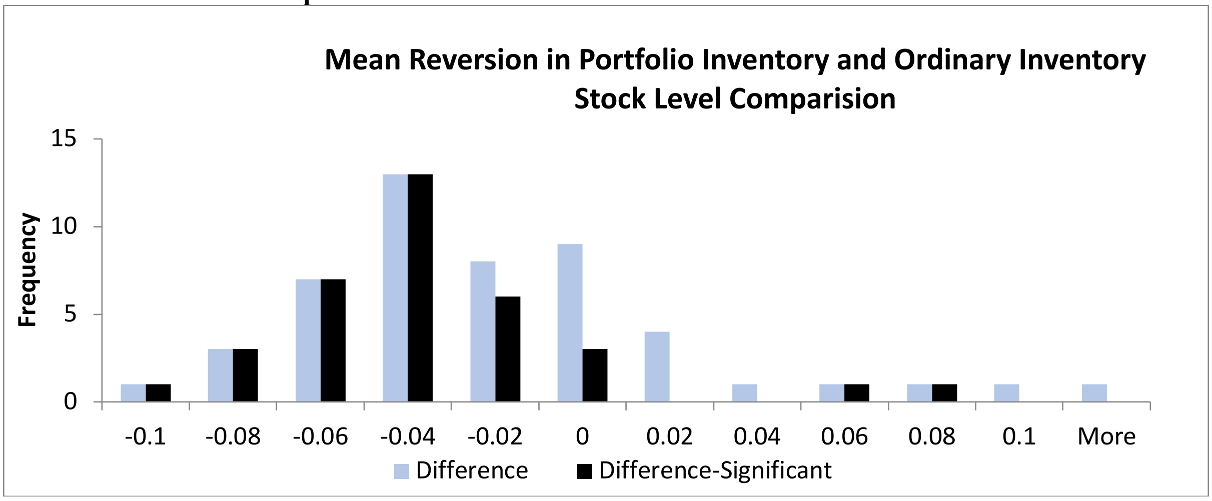
Figures and Tables

Figure 1: Mean Reversion in Ordinary v/s Portfolio Inventories

This figure presents the distribution of the difference in the rates of mean reversion in relative ordinary and portfolio inventories of Voluntary Liquidity Providers (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($prelinv_{j,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. The differences in the rates of mean reversion in $invrel_{j,i,t}$ and $pinvrel_{i,t}$ are aggregated at the stock level in *Panel A* and at the trader level in *Panel B*. The dark bars indicate incidence of statistically significant differences (at 5% level).

Panel A: Stock Level Comparison



Panel B: Trader Level Comparison

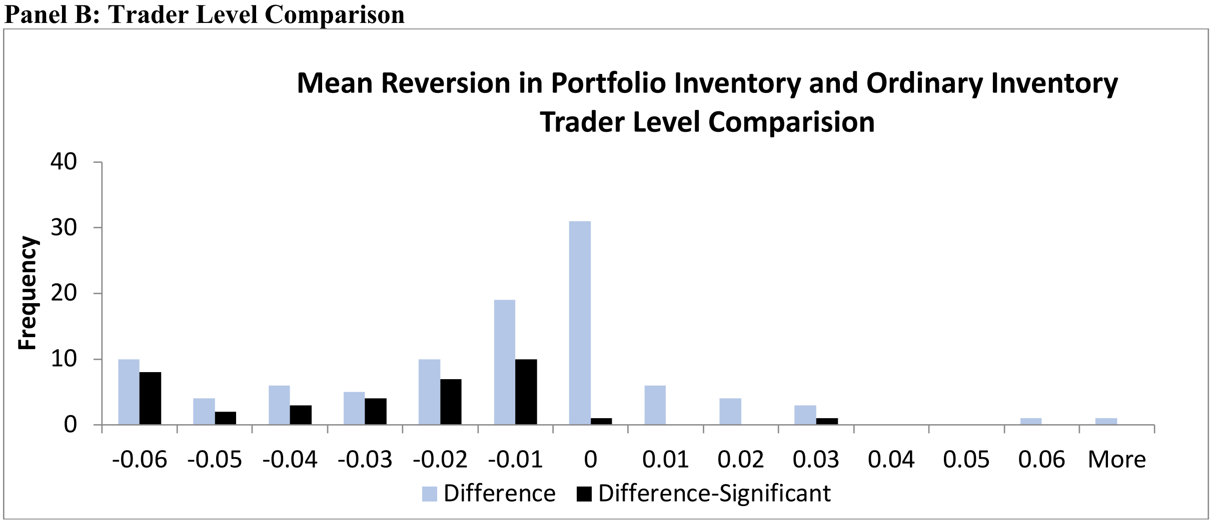
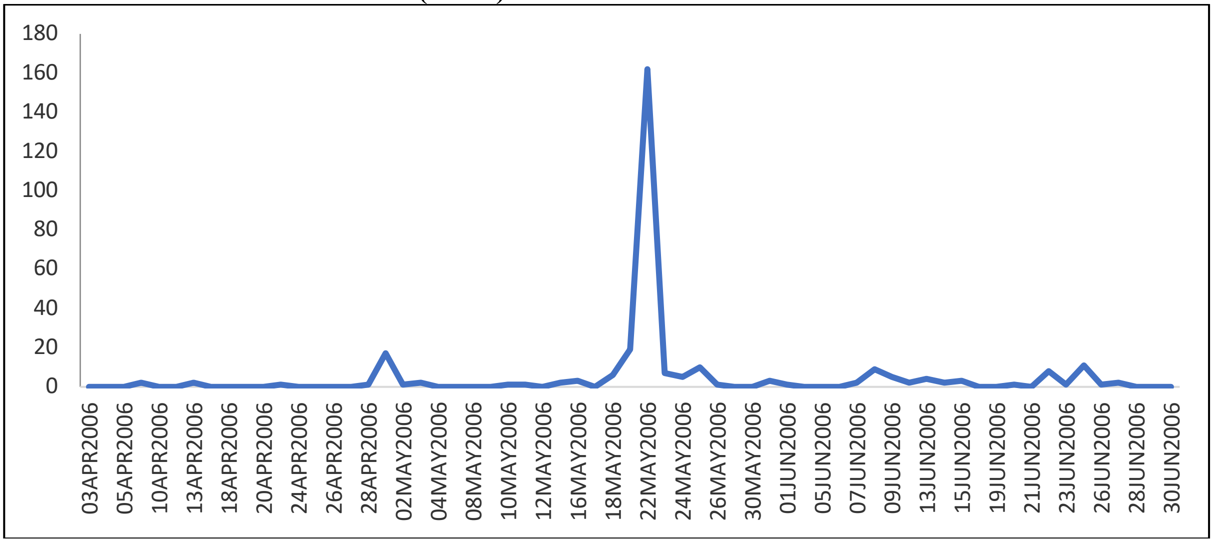


Figure 2: Stressful Episodes

This figure presents the aggregate number of daily stressful episodes in the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India during our sample period, April to June, 2006. Panel A presents aggregate number of daily extreme price movements (EPMs) - defined as intervals that belong to the 99.9th percentile of 1-second absolute mid-quote return for each stock. Panel B presents aggregate number of daily jumps, which are identified using methodology developed in Lee and Mykland (2008).

Panel A: Extreme Price Movements (EPMs)



Panel B: Jumps

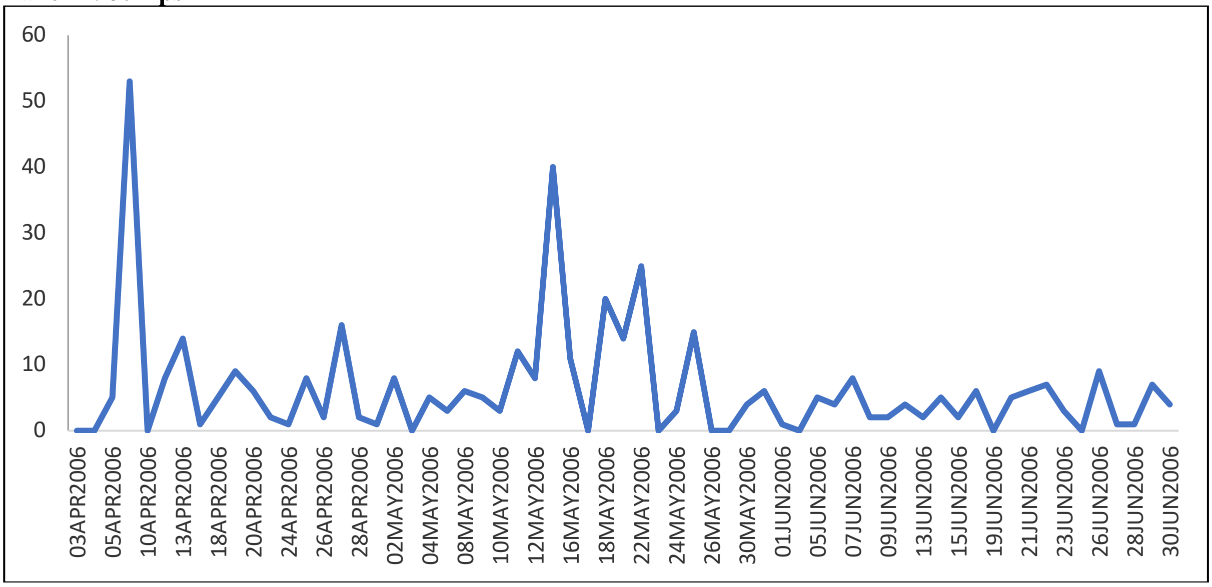


Figure 3: Stressful Episodes Impulse Responses

This figure presents the cumulative impulse response functions of changes in extreme price movements $\Delta nrextreme$ and changes in the number of transient jumps $\Delta nrjumps$ to shocks in $pinvrange$ and $|pinvav_{i,t}|$ based on the following VAR(p) model:

$$y_{i,t} = A_0 + A_1 y_{i,t-1} + \cdots + A_p y_{i,t-p} + u_{i,t},$$

where the verctor y_t takes one of the following specification for EPMs (Panel A) :

$$y_{i,t} = [\Delta nrextreme_{i,t}, invrange_{i,t}, pinvrange_{i,t}, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|]^T,$$

$$y_{i,t} = [\Delta nrextreme_{i,t}, |invav_{i,t}|, |pinvav_{i,t}|, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|]^T,$$

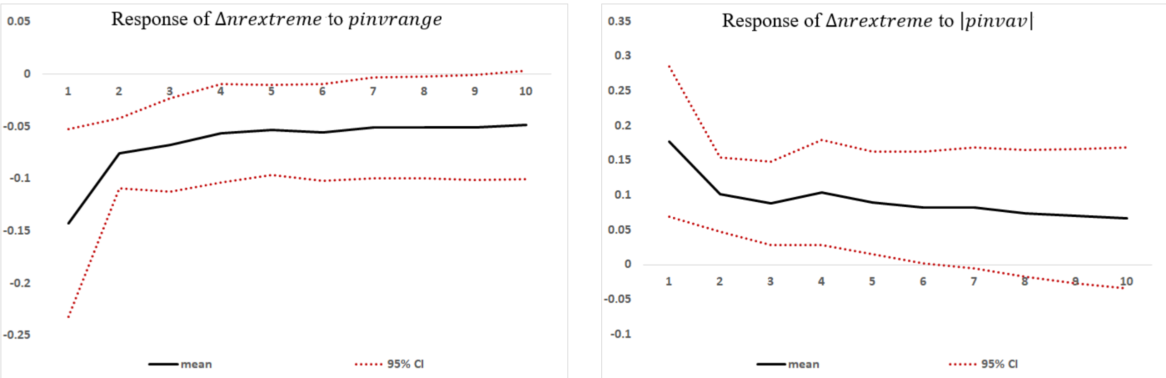
and one of the following specifications for transient jumps (Panel B):

$$y_{i,t} = [\Delta nrjumps_{i,t}, invrange_{i,t}, pinvrange_{i,t}, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|]^T,$$

$$y_{i,t} = [\Delta nrjumps_{i,t}, |invav_{i,t}|, |pinvav_{i,t}|, volatility_{i,t}, volume_{i,t}, |oib_{i,t}|]^T.$$

Extreme price movements are defined as periods that belong to the 99.9th percentile of 1-second absolute mid-quote return for each stock. $nrextreme_{i,t}$ is the number of extreme price movements in a stock in a 30-minute interval. Jumps are identified using the Lee and Mykland (2008) methodology. $nrjump_{i,t}$ is the number of jumps in stock i in a 30-minute interval. All the following variables are calculated over 30-minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ is defined analogously. $invav_{i,t}$ ($pinvav_{i,t}$) is the average trader's $inv_{j,i,t}$ ($pinv_{j,i,t}$) in a given time period. $volatility_{i,t}$ is the standard deviation of 1 minute stock returns, $volume_{i,t}$ is the trading volume, and $|oib_{i,t}|$ is the absolute value of trade imbalance. The model is estimated on the stock-by-stock level and the choice of value p is based on AIC criterion. Black solid line plots mean values of impulse responses across all stocks and the red dotted line corresponds to the 95% confidence interval. The sample consists of the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India during our sample period, April to June, 2006.

Panel A: Extreme Price Movements



Panel B: Jumps

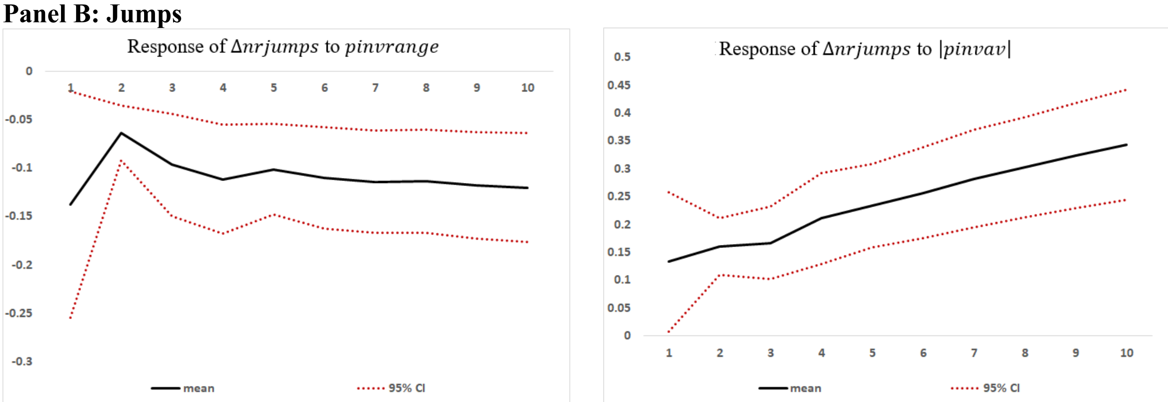


Table 1: Sample Descriptive Statistics

This table presents descriptive statistics of Voluntary Liquidity Provider's (VLPs) and stock characteristics. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. Panel A presents descriptive statistics of stock characteristics. *Number of Trades* is the average number of trades in a stock in the sample; it is first calculated over 30 minute intervals for each stock and then averaged across the 50 stocks in the sample. *Volume of Trades*, *Number of Orders* and *Volume of Orders* are calculated analogously. *Buy Depth* and *Sell Depth* are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. *Diff Depth* is *Buy Depth* minus *Sell Depth,* expressed as the ratio of the average depth. *Diff Depth*, *BidAsk Spread* (estimated from the order book, expressed as a ratio of the mid-quote), *Return* (total stock return) and *Volatility* (standard deviation of *Return*) are first calculated over 30 minute intervals for each stock and then averaged across the 50 stocks in the sample. Panel B presents descriptive statistics of Voluntary Liquidity Provider's (VLPs) characteristics. *Proportion of Trading Volume* is the average proportion of trading volume involving VLPs; it is calculated over 30 minute intervals. *Proportion of Number of Trades*, *Proportion of Limit Order Volume* and *Proportion of Number of Limit Orders* are analogously defined. *Churning Ratio* is the ratio of VLP's end-of-day inventory and daily trading volume; it is calculated first for each stock and then averaged across the 50 stocks in the sample. *Aggressiveness* is the ratio of VLP's daily aggressive trading volume (trades where the VLP's places the aggressive order) and daily trading volume; it is calculated first for each stock and then averaged across the 50 stocks in the sample.

Panel A: Stock characteristics

	Mean	Median	Std. Dev.
Market Capitalization (USD Billions)	7	4	3
Number of Trades	1,303	910	1165
Volume of Trades	121,343	48,294	174,902
Number of Orders	1,678	1,150	1,450
Volume of Orders	469,357	207,827	608,518
Bid-Ask Spread	0.03%	0.02%	0.03%
Difference Depth	0.26%	0.20%	10.19%
Volatility	0.43%	0.42%	0.07%
Return	-0.02%	-0.02%	0.02%

Panel B: Limit Order Book traders characteristics

	Mean	Median	Std. Dev.
Proportion of Trading Volume	47.10%	49.76%	10.47%
Proportion of Number of Trades	55.96%	57.08%	9.77%
Proportion of Limit Order Volume	43.59%	46.47%	10.56%
Proportion of Number of Limit Orders	37.88%	39.15%	10.49%
Churning Ratio	3.02%	0.00%	6.84%
Aggressiveness	49.42%	49.68%	8.41%

Table 2: Mean Reversion in Relative Inventories

This table presents results from the analysis of mean reversion in relative inventories (Panel A) and relative portfolio inventories (Panel B) of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. $\Delta invrel_{j,i,t}$ (defined as $invrel_{j,i,t} - invrel_{j,i,t-1}$) is the dependent variable in all specifications. Portfolio inventory ($tpinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($tpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta tpinvrel_{j,i,t}$ (defined as $tpinvrel_{j,i,t} - tpinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ *(*stock return)*,* $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume)*,* $volatility_{i,t}$ (standard deviation of 1 minute returns)*,* $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_{t-1}$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $tpinvrel_{j,i,t-1}$ for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t-1}$ is a dummy variable equal to 1 when $volatility_{i,t-1}$ is 2 standard deviations greater than its mean. $loss_{j,t-1}$ is a dummy variable equal to 1 when a trader's 30-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ordinary inventory

Intercept	0.000	0.000	0.001	0.001	0.000	0.000
$invrel_{j,i,t-1}$	-0.081***	-0.083***	-0.060***	-0.028***	-0.080***	-0.078***
$ret_{i,t-1}$		0.001	0.001	0.001	0.001	0.000
$oib_{i,t-1}$		-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
$volatility_{i,t-1}$		-0.001*	-0.001*	-0.001*	-0.001**	-0.001**
$spread_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volume_{i,t-1}$		0.002***	0.002***	0.002***	0.002***	0.002***
$invrel_{j,i,t-1} \times peak_{t-1}$			-0.054***			
$invrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.066***		
$invrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.063***	
$invrel_{j,i,t-1} \times loss_{j,t-1}$						-0.039***
N	3,459,372	3,381,472	3,381,472	3,381,472	3,381,472	3,381,472
Adj R-Square	4.21%	4.31%	4.75%	4.71%	4.40%	4.41%

Panel B: Portfolio inventory

Intercept	0.004***	0.004***	0.004***	0.006***	0.004***	0.004***
$tpinvrel_{j,i,t-1}$	-0.111***	-0.113***	-0.084***	-0.070***	-0.111***	-0.107***
$ret_{i,t-1}$		0.001	0.001	0.001	0.001	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	-0.001
$volatility_{i,t-1}$		-0.001	-0.001	-0.001	0.000	-0.001
$spread_{i,t-1}$		0.001	0.001	0.001	0.001	0.001
$volume_{i,t-1}$		0.000	0.000	0.001	0.000	0.001
$tpinvrel_{j,i,t-1} \times peak_{t-1}$			-0.077***			
$tpinvrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.115***		
$tpinvrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.062***	
$tpinvrel_{j,i,t-1} \times high_{j,t-1}$						-0.132***
N	3,459,372	3,381,472	3,381,472	3,381,472	3,381,472	3,381,472
Adj R-Square	5.83%	5.93%	6.58%	7.37%	5.99%	6.28%

Table 3: Determinants of Mean Reversion in Inventories

This table presents results from the analysis of the difference between the rates of mean reversion in the Voluntary Liquidity Providers' (VLPs) portfolio and ordinary inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. fin_j is a dummy variable equal to 1 if the VLP j is identified as a financial institutional trader in the dataset. $active_j$ is a dummy variable equal to 1 if the VLP is the one of the 10 most active (in terms of number of limit orders posted) VLPs. $aggressiveratio_j$ is the ratio of an VLP's daily aggressive trading volume (trades where the VLP's places the aggressive order) and daily total trading volume. All variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($tpinv_{j,i,t}$) is a trader's total inventory in that stock defined as $inv_{j,i,t}$ plus the rest of the portfolio inventory weighted by the corresponding cross-stocks betas. All inventory variables are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. Relative portfolio inventory ($tpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Mean reversion in $tpinvrel_{j,i,t}$ and $invrel_{j,i,t}$ are calculated by estimating the following regressions:

$$\Delta invrel_{j,i,t} = \alpha_0 + \alpha_1 invrel_{j,i,t-1} + u_{j,i,t},$$
$$\Delta tpinvrel_{j,i,t} = \alpha_0 + \alpha_1 tpinvrel_{j,i,t-1} + u_{j,i,t}.$$

The difference between the rates of mean reversion in portfolio and ordinary of the VLPs is the dependent variable in both the panels. In Panel A, the differences in inventory mean reversions are aggregated at the trader level; and in Panel B, the same differences are aggregated at the stock level. $spread_i$ (estimated from the order book, expressed as a ratio of the mid-quote), $volatility_i$ (standard deviation of 1 minute returns) and $volume_i$ (trading volume) are calculated as averages of each of the 50 stocks in the sample. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trader level regression

Intercept	-0.063***
fin_j	0.027***
$active_j$	-0.017
$aggressivratio_j$	0.029**
N	100
Adj R-Square	4.13%

Panel B: Stock level regression

Intercept	-0.065*
$spread_i$	-0.325*
$volume_i$	0.000
$volatility_i$	7.338
N	50
Adj R-Square	5.14%

Table 4: Quoting Regimes and Relative Portfolio Inventories

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) different quoting regimes (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. Panel A presents results of multinomial logit regressions with three (limit order) quoting regimes: when a trader places only buy orders (*Buy Orders Only*); when a trader places only sell orders (*Sell Order Only*); and when a trader is indifferent between the two sides, either present in both or absent in both (*Buy and Sell or NoOrders*). The third regime is used as the base case to which the first two are compared. Panel B presents results of logit regressions with only two (limit order) quoting regimes: *Sell Orders Only* and *Buy Orders Only. Buy Orders Only* used as the base case. All the variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (total stock return), $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock, fin_j is a dummy variable equal to 1 if the VLP is a financial institutional trader. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Three quoting regimes

Intercept	*Sell Orders Only*	-3.897***	-3.880***	-3.900***	-3.883***	-3.907***
	Buy Orders Only	-3.657***	-3.639***	-3.657***	-3.639***	-3.674***
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.103***	0.102***	0.105***	0.103***	0.104***
	Buy Orders Only	-0.034***	-0.034***	-0.034***	-0.034***	-0.035***
$pinvrel_{j,i,t-1}$	*Sell Orders Only*			0.052***	0.051***	0.050***
	Buy Orders Only			0.001	0.002	-0.013***
$pinvrel_{j,i,t-1}$	*Sell Orders Only*					0.010
$\times fin_j$	*Buy Orders Only*					0.098***
$ret_{i,t-1}$	*Sell Orders Only*		-0.007*		-0.007*	-0.007*
	Buy Orders Only		0.026***		0.026***	0.026***
$volume_{i,t-1}$	*Sell Orders Only*		0.046***		0.046***	0.046***
	Buy Orders Only		0.063***		0.063***	0.063***
$oib_{i,t-1}$	*Sell Orders Only*		0.002		0.002	0.002
	Buy Orders Only		-0.007**		-0.007**	-0.007**
fin_j	*Sell Orders Only*					0.223***
	Buy Orders Only					0.307***
N		3,459,372	3,381,472	3,459,372	3,381,472	3,381,472
Pseudo R-Sq.		0.03%	0.05%	0.04%	0.05%	0.09%

Panel B: Two quoting regimes

Intercept	*Sell Orders Only*	0.086***	0.084***	0.085***	0.083***	0.097***
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.102***	0.103***	0.104***	0.105***	0.106***
$pinvrel_{j,i,t-1}$	*Sell Orders Only*			0.066***	0.064***	0.072***
$pinvrel_{j,i,t-1} \times fin_j$	*Sell Orders Only*					0.034**
$ret_{i,t-1}$	*Sell Orders Only*		0.123***		0.122***	0.123***
$volume_{i,t-1}$	*Sell Orders Only*		-0.082***		-0.082***	-0.080***
$oib_{i,t-1}$	*Sell Orders Only*		-0.004		-0.005	-0.004
fin_j	*Sell Orders Only*					-0.111***
N		19,438	19,438	19,438	19,438	19,438
Pseudo R-Square		0.90%	1.03%	0.61%	1.15%	1.31%

Table 5: Trader Order Imbalances and Relative Inventories

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) order imbalances (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $trader\ oib_{j,i,t}$, the dependent variable, is a trader's order imbalance (buy-initiated minus sell-initiated trader's total order volume, expressed as a ratio of trader's total order volume) in a given stock during a given time interval; it is standardized by trader and stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (total stock return), $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock, fin_j equals to one if VLP j is a financial institutional trader and zero otherwise. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.004	-0.013**	0.005	-0.013**	-0.012**
$invrel_{j,i,t-1}$	-0.046***	-0.044***	-0.047***	-0.045***	-0.045***
$pinvrel_{j,i,t-1}$			-0.022***	-0.023***	-0.021***
$pinvrel_{j,i,t-1} \times fin_j$					0.016***
$trader\ oib_{j,i,t-1}$		0.135***		0.135***	0.136***
$ret_{i,t-1}$		0.005		0.005	0.005
$volume_{i,t-1}$		0.011***		0.011***	0.011***
$oib_{i,t-1}$		-0.011***		-0.012***	-0.011***
fin_j					-0.005
N	729,256	551,005	729,256	551,005	551,005
Adj R-Square	0.67%	2.60%	0.73%	2.66%	2.64%

Table 6: Bid-Ask Spreads and Portfolio Inventories

This table presents results from the analysis of bid-ask spreads and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $spread$ (estimated from the order book, expressed as a ratio of the mid-quote) is the dependent variable in all specifications. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ is defined analogously. $volatility_{i,t}$ (standard deviation of 1 minute returns) and $volume_{i,t}$ (trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $pspread_{i,t}$ is the equal weighted average bid-ask spread of the rest of the 49 stocks in the Nifty index. $|oibfin_{i,t-1}|$ and $|poibfin_{i,t-1}|$ denote absolute value of order imbalances and portfolio order imbalances of financial institutions respectively. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.199***	0.032	-0.123***	-0.084***
$invrange_{i,t-1}$	-0.008	0.006		
$pinvrange_{i,t-1}$	-0.222***	-0.095***		
$\|invav_{i,t-1}\|$			-0.058	-0.049
$\|pinvav_{i,t-1}\|$			0.212***	0.048*
$volatility_{i,t-1}$		0.017**		0.017**
$volume_{i,t-1}$		0.038***		0.038***
$open\ close_{t-1}$		0.044***		0.047***
$pspread_{i,t-1}$		0.124***		0.124***
$\|oibfin_{i,t-1}\|$		-0.002		-0.002
$\|poibfin_{i,t-1}\|$		0.033***		0.033***
N	33,060	32,908	33,060	32,908
Adj R-Square	0.58%	5.13%	0.60%	5.08%

Table 7: Portfolio Inventories and Depth of Limit Order Book

This table presents results on the effect of Voluntary Liquidity Providers' (VLPs) inventories on depth of the Limit Order Book (LOB). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $buy\ depth_{i,t}$ and $sell\ depth_{i,t}$ are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. $diff\ depth_{i,t}$, the dependent variable, is $buy\ depth_{i,t}$ minus $sell\ depth_{i,t}$ divided by the average depth; it is standardized by each stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invav_{i,t}$ is the average trader $inv_{j,i,t}$ in a given time period; it is standardized by stock. $pinvav_{i,t}$ is defined analogously. $ret_{i,t}$ (total stock return) and $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) are standardized for each stock. $diff\ pdepth_{i,t}$ is the equal weighted average $diff\ depth_{i,t}$ of the rest of the 49 stocks in the Nifty index. $poibfin_{i,t-1}$ is portfolio order imbalance of financial institutions. Standard errors are clustered by firm and date. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.025***	0.026***	0.026***
$invav_{i,t-1}$	-0.135***	-0.126	-0.116***
$pinvav_{i,t-1}$	-0.131***	-0.129***	-0.043***
$ret_{i,t-1}$		0.036***	0.036***
$oib_{i,t-1}$		0.102***	0.100***
$diff\ pdepth_{i,t-1}$			0.057***
$poibfin_{i,t-1}$			0.027***
N	32,966	32,814	32,814
Adj R-Square	0.79%	2.13%	2.83%

Table 8: Pricing Errors and Portfolio Inventories

This table presents results on effects of and Voluntary Liquidity Providers' (VLPs) portfolio inventories on price pressures. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. For each stock i we estimate the state-space model of the price series $p_{i,t} = m_{i,t} + s_{i,t}$, where the efficient price series follows a random walk with a drift $m_{i,t} = m_{i,t-1} + \beta_{im} r_t^M + w_{i,t}$ and the process for the stationary pricing error follows $s_{i,t} = \alpha_i invav_{i,t} + \delta_i pinvav_{i,t} + \beta_{is} r_t^M + u_{i,t}$. The error term $u_{i,t}$ is normally distributed and uncorrelated with $w_{i,t}$. The r_t^M term captures the adjustment to common factor innovation and is computed as the demeaned market return. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invav_{i,t}$ is the average trader $inv_{i,t}$. $pinvav_{i,t}$ is the average trader $pinv_{j,i,t}$ in a given time period; it is standardized by stock. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ is defined analogously. The dummy variable $dinv_{i,t}$ that is equal to 1 if the inventory inter-quartile range $invrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. Similarly, $dpinv_{i,t}$ is equal to 1 if the inventory inter-quartile range $pinvrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. The Table presents the averages of the estimated coefficients across 50 stocks. Two tailed p-values are also reported.

$invav_{i,t}$	-28.32***	-43.53***	-36.30*	-23.38***
$invav_{i,t} \times invrange_{i,t}$		14.59		
$invav_{i,t} \times (invrange_{i,t})^2$			-0.15	
$invav_{i,t} \times dinv_{i,t}$				-8.03***
$pinvav_{i,t}$	-5.40*	-14.82*	-11.30**	-2.60
$pinvav_{i,t} \times pinvrange_{i,t}$		7.12		
$pinvav_{i,t} \times (pinvrange_{i,t})^2$			3.29*	
$pinvav_{i,t} \times dpinv_{i,t}$				-2.15**
$r_t^M(\beta_m)$	1.03***	1.02***	1.02***	1.03***
$r_t^M(\beta_s)$	-0.05***	-0.06***	-0.06***	-0.06***

Table 9: Market Fragility and Portfolio Inventories

This table presents the effects of Voluntary Liquidity Providers' (VLPs) inventories on likelihood of extreme price movements (Panel A) and price jumps (Panel B). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange, India from April to June 2006. Extreme price movements are defined as periods that belong to the 99.9th percentile of 1-second absolute mid-quote return for each stock. For Logit regressions, the dependent (binary) variable $extreme_{i,t}$ is equal one when a stock has an EPM in a 30-minute interval. For Tobit recreations, the dependent variable $nrextreme_{i,t}$ is the number of EPMs in a stock in a 30-minute interval. Jumps are identified using the Lee and Mykland (2008) methodology. For Logit regressions, the dependent (binary) variable $jump_{i,t}$ is equal one when a stock has experienced a jump in a 30-minute interval. For Tobit regressions, the dependent variable $nrjump_{i,t}$ is the number of jumps in stock i in a 30-minute interval. All the following variables are calculated over 30-minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ is defined analogously. $invav_{i,t}$ ($pinvav_{i,t}$) is the average trader's $inv_{j,i,t}$ ($pinv_{j,i,t}$) in a given time period; it is standardized by stock. $volatility_{i,t}$ (standard deviation of 1 minute stock returns), $volume_{i,t}$ (trading volume), and $|oib_{i,t}|$ (absolute value of trade imbalance) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $|poibfin_{i,t-1}|$ is the absolute value of portfolio order imbalances of financial institutions. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level.

Panel A: Extreme price movements

	Logit Regressions		Tobit Regressions	
Intercept	-4.323***	-7.210***	-5.535***	-8.657***
$invrange_{i,t-1}$	-0.971***		-1.023**	
$pinvrange_{i,t-1}$	-1.365***		-1.586***	
$\|invav_{i,t-1}\|$		-0.830		-1.116
$\|pinvav_{i,t-1}\|$		2.725***		2.967***
$volatility_{i,t-1}$	0.412***	0.371***	0.604***	0.548***
$volume_{i,t-1}$	0.109*	0.132***	0.154**	0.155**
$\|oib_{i,t-1}\|$	-0.001	-0.046	-0.001	-0.029
$open\ close_{t-1}$	0.406**	0.559***	0.428***	0.632***
$extreme_{i,t-1}$	0.671***	0.466***		
$nrextreme_{i,t-1}$			1.162**	0.950*
$\|poibfin_{i,t-1}\|$	0.680***	0.507***	0.785***	0.600***
N	32,908	32,908	32,908	32,908
Wald Test (p-value)	<0.01	<0.01	<0.01	<0.01

Panel B: Price jumps

	Logit Regressions		Tobit Regressions	
Intercept	-5.340***	-3.874***	-7.907***	-6.116***
$invrange_{i,t-1}$	-0.724***		-0.906***	
$pinvrange_{i,t-1}$	-1.509***		-1.945***	
$\|invav_{i,t-1}\|$		-0.259		-0.346
$\|pinvav_{i,t-1}\|$		0.369**		0.577***
$volatility_{i,t-1}$	0.101***	0.061**	0.136***	0.081***
$volume_{i,t-1}$	-0.00	-0.005	0.015	0.020
$\|oib_{i,t-1}\|$	-0.041	0.036	-0.057	0.056
$open\ close_{t-1}$	0.289**	0.221***	0.357***	0.268***
$jump_{i,t-1}$	1.015***	1.086***		
$nrjump_{i,t-1}$			1.381***	1.504***
$\|poibfin_{i,t-1}\|$	0.446***	0.400***	0.581***	0.527
N	35,265	35,265	35,265	35,265
Wald Test (p-value)	<0.01	<0.01	<0.01	<0.01

<u>Internet Appendix</u>

Correlated Portfolio Inventory Risk of Liquidity Providers: Frictions and Market Fragility

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This appendix presents supplementary results not included in the main body of the paper.

This appendix is not for publication.

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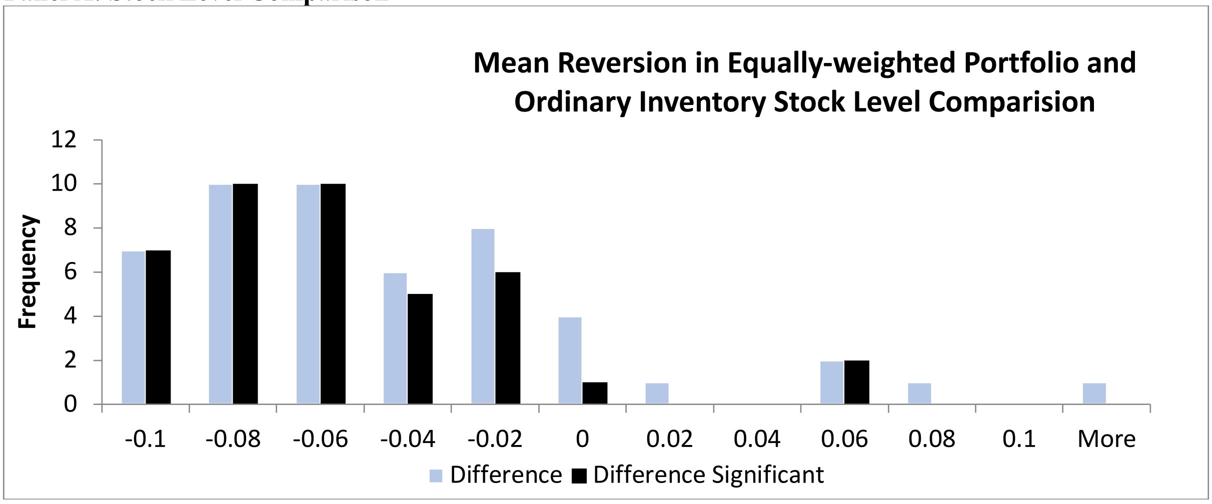
Internet Appendix A

Figure A1: Mean Reversion in Ordinary v/s Equally Weighted Portfolio Inventories

This figure presents the distribution of the difference in the rates of mean reversion in relative ordinary and equally weighted portfolio inventories of Voluntary Liquidity Providers (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. **Equally weighted** portfolio inventory ($EWpinv_{i,t}$) is a sum of trader's inventory in each stock in the portfolio, standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{i,t}$) is calculated as a trader's standardized equally weighted portfolio inventory minus the median standardized equally weighted portfolio inventory in a stock. The differences in the rates of mean reversion in $invrel_{j,i,t}$ and $EWpinvrel_{i,t}$ are aggregated at the stock level in Panel A and at the trader level in Panel B. The dark bars indicate incidence of statistically significant differences (at 5% level).

Panel A: Stock Level Comparison



Panel B: Trader Level Comparison

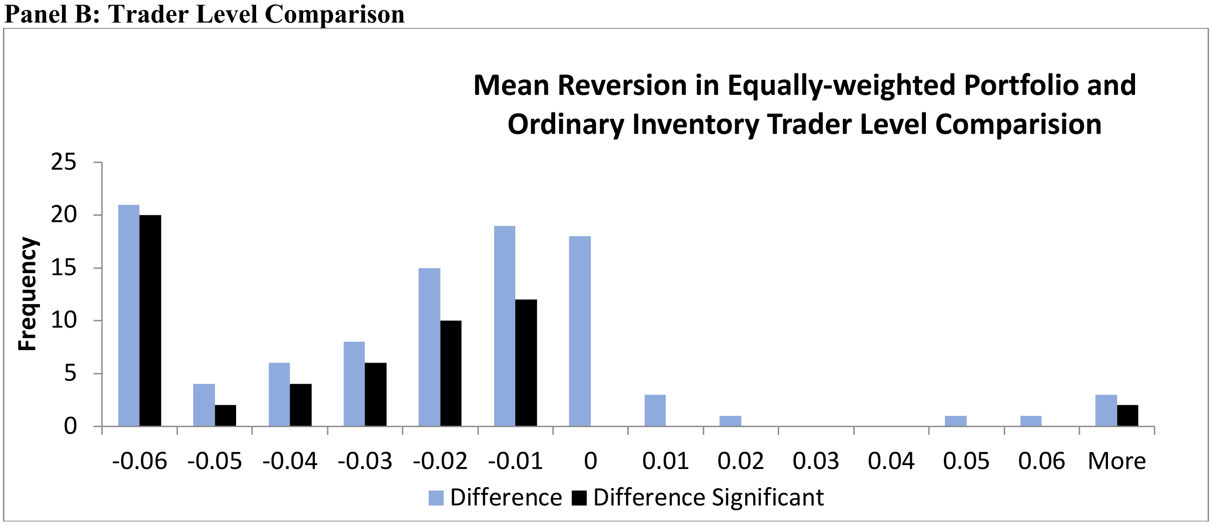


Table A1: Mean Reversion in Relative Equally weighted Portfolio Inventories

This table presents results from the analysis of mean reversion in relative equally weighted portfolio inventories of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Equally weighted portfolio inventory ($EWpinv_{j,t}$) is a sum of trader's inventory in all stocks in the portfolio. All inventory variables are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWprelinv_{j,i,t}$) is calculated as a trader's standardized equally weighted portfolio inventory minus the median standardized equally weighted portfolio inventory in a stock. $\Delta EWpinvrel_{j,i,t}$ (defined as $EWpinvrel_{j,i,t} - EWpinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume), $volatility_{i,t}$ (standard deviation of 1 minute returns), $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_{t-1}$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $EWpinvrel_{j,i,t-1}$ for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t-1}$ is a dummy variable equal to 1 when $volatility_{i,t-1}$ is 2 standard deviations greater than its mean. $loss_{j,t-1}$ is a dummy variable equal to 1 when a trader's 30-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.004**	0.004**	0.004**	0.006**	0.004**	0.005**
$EWpinvrel_{j,i,t-1}$	-0.120***	-0.122***	-0.091***	-0.080***	-0.120***	-0.111***
$ret_{i,t-1}$		0.001	0.000	0.000	0.000	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.001	0.001	0.000	0.000	0.000
$volume_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$EWpinvrel_{j,i,t-1} \times peak_{t-1}$			-0.085***			
$EWpinvrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.147***		
$EWpinvrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.082***	
$EWpinvrel_{j,i,t-1} \times loss_{j,t-1}$						-0.084***
N	3,459,372	3,381,472	3,381,472	3,381,472	3,381,472	3,381,472
Adj R-Square	6.29%	6.38%	7.11%	8.28%	6.61%	6.71%

Table A2: Determinants of Mean Reversion in Inventories

This table presents results from the analysis of the difference between the rates of mean reversion in the Voluntary Liquidity Providers' (VLPs) equally weighted portfolio inventories and ordinary inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. fin_j is a dummy variable equal to 1 if the VLP is a financial institutional trader. $active_j$ is a dummy variable equal to 1 if the VLP is the one of the 10 most active (in terms of number of limit orders posted) VLPs. $aggressiveratio_j$ is the ratio of an VLP's daily aggressive trading volume (trades where the VLP's places the aggressive order) and daily total trading volume. All variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted total portfolio inventory ($TEWpinv_{j,i,t}$) is a trader's total equally-weighted inventory in the entire portfolio. All inventory variables are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. Relative total equally weighted portfolio inventory ($TEWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Mean reversion in $TEWpinvrel_{j,i,t}$ and $invrel_{j,i,t}$ are calculated by estimating the following regressions:

$$\Delta invrel_{j,i,t} = \alpha_0 + \alpha_1 invrel_{j,i,t-1} + u_{j,i,t},$$

$$\Delta TEWpinvrel_{j,i,t} = \alpha_0 + \alpha_1 TEWpinvrel_{j,i,t-1} + u_{j,i,t}.$$

The difference between the rates of mean reversion in portfolio and ordinary of the VLPs is the dependent variable in both the panels. In Panel A, the differences in inventory mean reversions are aggregated at the trader level; and in Panel B, the same differences are aggregated at the stock level. $spread_i$ (estimated from the order book, expressed as a ratio of the mid-quote), $volatility_i$ (standard deviation of 1 minute returns) and $volume_i$ (trading volume) are calculated as averages of each of the 50 stocks in the sample. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trader level regression

Intercept	-0.054***
fin_j	0.028***
$active_j$	-0.016
$aggressivratio_j$	0.058**
N	100
Adj R-Square	6.15%

Panel B: Stock level regression

Intercept	-0.103***
$spread_i$	-0.419***
$volume_i$	0.000*
$volatility_i$	13.022
N	50
Adj R-Square	10.31%

Table A3: Quoting Regimes and Relative Equally-weighted Inventories

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) different quoting regimes (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. Panel A presents results of multinomial logit regressions with three (limit order) quoting regimes: when a trader places only buy orders (*Buy Orders Only*); when a trader places only sell orders (*Sell Order Only*); and when a trader is indifferent between the two sides, either present in both or absent in both. The third regime is used as the base case to which the first two are compared. Panel B presents results of logit regressions with only two (limit order) quoting regimes: *Sell Order Only* and *Buy Orders Only*, used as the base case. All the variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $EWpinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock. fin_j is a dummy variable equal to 1 if the VLP is a financial institutional trader. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Three quoting regimes

Intercept	*Sell Orders Only*	-3.900***	-3.883***	-3.908***
	Buy Orders Only	-3.656***	-3.639***	-3.674***
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.105***	0.104***	0.104***
	Buy Orders Only	-0.035***	-0.035***	-0.035***
$EWpinvrel_{j,i,t-1}$	*Sell Orders Only*	0.050***	0.049***	0.054***
	Buy Orders Only	-0.009***	-0.007*	-0.018***
$EWpinvrel_{j,i,t-1} \times fin_j$	*Sell Orders Only*			-0.036***
	Buy Orders Only			0.073***
$ret_{i,t-1}$	*Sell Orders Only*		-0.007**	-0.007*
	Buy Orders Only		0.026***	0.026***
$volume_{i,t-1}$	*Sell Orders Only*		0.046***	0.046***
	Buy Orders Only		0.063***	0.063***
$oib_{i,t-1}$	*Sell Orders Only*		0.002	0.002
	Buy Orders Only		-0.007**	-0.007**
fin_j	*Sell Orders Only*			0.226***
	Buy Orders Only			0.310***
N		3,459,372	3,381,472	3,381,472
Pseudo R-Square		0.04%	0.05%	0.09%

Panel B: Two quoting regimes

Intercept	*Sell Orders Only*	0.085***	0.083***	0.097***
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.105***	0.106***	0.107***
$EWpinvrel_{j,i,t-1}$	*Sell Orders Only*	0.079***	0.077***	0.082***
$EWpinvrel_{j,i,t-1} \times fin_j$	*Sell Orders Only*			-0.023**
$ret_{i,t-1}$	*Sell Orders Only*		0.122***	0.123***
$volume_{i,t-1}$	*Sell Orders Only*		-0.081***	-0.079***
$oib_{i,t-1}$	*Sell Orders Only*		-0.004	-0.004
fin_j	*Sell Orders Only*			-0.109
N		19,438	19,438	19,438
Pseudo R-Square		0.65%	1.19%	1.23%

Table A4: Trader Order Imbalances and Relative Equally-weighted Portfolio Inventories

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) order imbalances (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $trader\ oib_{j,i,t}$, the dependent variable, is a trader's order imbalance (buy-initiated minus sell-initiated trader's total order volume, expressed as a ratio of trader's total order volume) in a given stock during a given time interval; it is standardized by trader and stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $EWpinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. fin_j is a dummy variable equal to 1 if the VLP is a financial institutional trader. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.005	-0.012**	-0.012*
$invrel_{j,i,t-1}$	-0.047***	-0.045***	-0.045***
$EWpinvrel_{j,i,t-1}$	-0.024***	-0.025***	-0.027***
$EWpinvrel_{j,i,t-1} \times fin_j$			0.019***
$trader\ oib_{j,i,t-1}$		0.136***	0.136***
$ret_{i,t-1}$		0.005	0.005
$volume_{i,t-1}$		0.011***	0.011***
$oib_{i,t-1}$		-0.011***	-0.011***
fin_j			-0.005
N	729,256	551,005	551,005
Adj R-Square	0.74%	2.65%	2.66%

Table A5: Bid-Ask Spreads and Equally-weighted Portfolio Inventories

This table presents results from the analysis of bid-ask spreads and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $spread_{i,t}$ (estimated from the order book, expressed as a ratio of the mid-quote) is the dependent variable in all specifications. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $EWpinvrange_{i,t}$ is defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{j,i,t}$ in a given time period; it is standardized by stock. $|EWpinvav_{i,t}|$ is defined analogously. $volatility_{i,t}$ (standard deviation of 1 minute returns) and $volume_{i,t}$ (trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $pspread_{i,t}$ is the equal weighted average bid-ask spread of the rest of the 49 stocks in the Nifty index. $|oibfin_{i,t-1}|$ and $|poibfin_{i,t-1}|$ are the absolute value of portfolio and stock order imbalances of financial institutions. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.253***	0.055*	-0.126***	-0.087***
$invrange_{i,t-1}$	-0.004	0.007		
$EWpinvrange_{i,t-1}$	-0.265***	-0.112***		
$\|invav_{i,t-1}\|$			-0.060*	-0.049
$\|EWpinvav_{i,t-1}\|$			0.217***	0.055**
$volatility_{i,t-1}$		0.016**		0.017**
$volume_{i,t-1}$		0.038***		0.038***
$open\ close_{t-1}$		0.043***		0.048***
$pspread_{i,t}$		0.122***		0.124***
$\|oibfin_{i,t-1}\|$		-0.002		-0.002
$\|poibfin_{i,t-1}\|$		0.033***		0.033***
N	33,060	32,908	33,060	32,908
Adj R-Square	0.78%	5.16%	0.66%	5.09%

Table A6: Equally-weighted Portfolio Inventories and Depth of Limit Order Book

This table presents results on the effect of Voluntary Liquidity Providers' (VLPs) inventories on of the Limit Order Book (LOB). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $buy\ depth_{i,t}$ and $sell\ depth_{i,t}$ are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. $diff\ depth_{i,t}$, the dependent variable, is $buy\ depth_{i,t}$ minus $sell\ depth_{i,t}$ divided by the average depth; it is standardized by each stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. $invav_{i,t}$ is the average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $EWpinvav_{i,t}$ is defined analogously. $ret_{i,t}$ (total stock return) and $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) are standardized for each stock. $diff\ pdepth_{i,t}$ is the equal weighted average $diff\ depth_{i,t}$ of the rest of the 49 stocks in the Nifty index. $poibfin_{i,t-1}$ is portfolio order imbalances of financial institutions. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.025***	0.026***	0.026***
$invav_{i,t-1}$	-0.132***	-0.124	-0.115***
$EWpinvav_{i,t-1}$	-0.132***	-0.131***	-0.046***
$ret_{i,t-1}$		0.036***	0.036***
$oib_{i,t-1}$		0.102***	0.100***
$diff\ pdepth_{i,t-1}$			0.056***
$poibfin_{i,t-1}$			0.026***
N	32,966	32,814	32,814
Adj R-Square	0.82%	2.16%	2.84%

Table A7: Pricing Errors and Equally-weighted Portfolio Inventories

This table presents results on effects of and Voluntary Liquidity Providers' (VLPs) portfolio inventories on price pressures. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. For each stock i we estimate the state-space model of the price series $p_{i,t} = m_{i,t} + s_{i,t}$, where the efficient price series follows a random walk with a drift $m_{i,t} = m_{i,t-1} + \beta_{im} r_t^M + w_{i,t}$ and the process for the stationary pricing error follows $s_{i,t} = \alpha_i invav_{i,t} + \delta_i EWpinvav_{i,t} + \beta_{is} r_t^M + u_{i,t}$. The error term $u_{i,t}$ is normally distributed and uncorrelated with $w_{i,t}$. The r_t^M term captures the adjustment to common factor innovation and is computed as the demeaned market return. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. $invav_{i,t}$ is the average trader $inv_{j,i,t}$ $pinvav_{i,t}$ is the average trader $pinv_{j,i,t}$ in a given time period; it is standardized by stock. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $EWpinvrange_{i,t}$ is defined analogously. The dummy variable $dinv_{i,t}$ that is equal to 1 if the inventory inter-quartile range $invrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. Similarly, $dEWpinv_{i,t}$ is equal to 1 if the inventory inter-quartile range $pinvrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. The Table presents the averages of the estimated coefficients across 50 stocks. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$invav_{i,t}$	-28.48***	-43.55***	-36.41***	-23.48***
$invav_{i,t} \times invrange_{i,t}$		14.44		
$invav_{i,t} \times (invrange_{i,t})^2$			-0.37	
$invav_{i,t} \times dinv_{i,t}$				-8.08***
$EWpinvav_{i,t}$	-4.27	-16.89**	-12.11**	-2.24
$EWpinvav_{i,t} \times EWpinvrange_{i,t}$		9.46**		
$EWpinvav_{i,t} \times (EWpinvrange_{i,t})^2$			3.32***	
$EWpinvav_{i,t} \times dEWpinv_{i,t}$				-2.68***
$r_t^M (\beta_m)$	1.02***	1.02***	1.02***	1.02***
$r_t^M (\beta_s)$	-0.05***	-0.06***	-0.06***	-0.05***

Table A8: Market Fragility and Equally-weighted Portfolio Inventories

This table presents the effects of VLPs inventories on likelihood of extreme price movements (Panel A) and price jumps (Panel B). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange, India from April to June 2006. Extreme price movements are defined as periods that belong to the 99.9th percentile of 1-second absolute mid-quote return for each stock. For Logit regressions, the dependent (binary) variable $extreme_{i,t}$ is equal one when a stock has experienced an EPM in a 30-minute interval. For Tobit regressions, the dependent variable $nrextreme_{i,t}$ is the number of EPMs experienced by a stock in a 30-minute interval. Jumps are identified using the Lee and Mykland (2008) methodology. For Logit regressions, the dependent (binary) variable $jump_{i,t}$ is equal one when a stock has experienced a Jump in a 30-minute interval. For Tobit regressions, the dependent variable $nrjump_{i,t}$ is the number of Jumps experienced by a stock in a 30-minute interval. All the following variables are calculated over 30-minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $EWpinvrange_{i,t}$ is defined analogously. $invav_{i,t}$ ($EWpinvav_{i,t}$) is the average trader's $inv_{j,i,t}$ ($EWpinv_{i,t}$) in a given time period; it is standardized by stock. $volatility_{i,t}$ (standard deviation of 1 minute stock returns), $volume_{i,t}$ (trading volume), and $|oib_{i,t}|$ (absolute value of order imbalance) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level.

Panel A: Extreme Price Movements

	Logit Regressions		Tobit Regressions	
Intercept	-3.808***	-7.204***	-4.899***	-8.642***
$invrange_{i,t-1}$	-0.958***		-1.012***	
$EWpinvrange_{i,t-1}$	-1.786***		-2.118***	
$\lvert invav_{i,t-1}\rvert$		-0.856		-1.142*
$\lvert EWpinvav_{i,t-1}\rvert$		2.681***		2.927***
$volatility_{i,t-1}$	0.404***	0.371***	0.593***	0.548***
$volume_{i,t-1}$	0.113*	0.128**	0.164**	0.151*
$\lvert oib_{i,t-1}\rvert$	-0.004	-0.047	-0.005	-0.031
$open\ close_{t-1}$	0.379**	0.494***	0.400*	0.628***
$extreme_{i,t-1}$	0.673*	0.486***		
$nrextreme_{i,t-1}$			1.161**	0.968***
$\lvert poibfin_{i,t-1}\rvert$	0.666***	0.551***	0.769***	0.586***
N	32,908	32,908	32,908	32,908
Wald Test (p-value)	<0.01	<0.01	<0.01	<0.01

Panel B: Price Jumps

	Logit Regressions		Tobit Regressions	
Intercept	-5.209***	-3.890***	-7.765***	-6.108***
$invrange_{i,t-1}$	-0.712***		-0.881***	
$EWpinvrange_{i,t-1}$	-1.380***		-1.790***	
$\|invav_{i,t-1}\|$		-0.261		-0.350
$\|EWpinvav_{i,t-1}\|$		0.411***		0.617***
$volatility_{i,t-1}$	0.103***	0.059**	0.140***	0.080**
$volume_{i,t-1}$	0.005	0.005	0.016	0.012
$\|oib_{i,t-1}\|$	0.042	0.035	0.060	0.058
$open\ close_{t-1}$	0.282***	0.222***	0.347***	0.272***
$jump_{i,t-1}$	1.024***	1.885***		
$nrjump_{i,t-1}$			1.397***	1.501***
$\|poibfin_{i,t-1}\|$	0.443***	0.396***	0.581***	0.523***
N	35,265	35,265	35,265	35,265
Wald Test (p-Value)	<0.01	<0.01	<0.01	<0.01

Table A9: Portfolio Inventories and Slope of Limit Order Book

This table presents results on the effect of Voluntary Liquidity Providers' (VLPs) portfolio inventories (Panel A) and equally-weighted portfolio inventories (Panel B) and slope of the Limit Order Book (LOB). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $buy\ slope_{i,t}$ is the ratio of the difference in the most aggressive buy-side limit order price and the 10th most aggressive buy-side limit order price and the total volume of the ten most aggressive limit orders on the buy side; $sell\ slope_{i,t}$ is defined analogously. $diff\ slope_{i,t}$, the dependent variable, is $buy\ slope_{i,t}$ minus $sell\ slope_{i,t}$ divided by the average slope; it is standardized by each stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $EWpinv_{j,i,t}$ is a trader's aggregate inventory in all stocks minus $inv_{j,i,t}$. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $invav_{i,t}$ is the average trader $inv_{j,i,t}$ in a given time period; it is standardized by stock. $pinvav_{i,t}$ and $EWpinvav_{i,t}$ are defined analogously. $ret_{i,t}$ (total stock return) and $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) are standardized for each stock. $diff\ pslope_{i,t}$ is the equal weighted average $diff\ slope_{i,t}$ of the rest of the 49 stocks in the Nifty index. $poibfin_{i,t-1}$ is portfolio order imbalance of financial institutions. Standard errors are clustered by firm and date. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolio inventory

Intercept	-0.010**	-0.012**	-0.011***
$invav_{i,t-1}$	0.105***	0.100***	0.097***
$pinvav_{i,t-1}$	0.064***	0.067***	0.066***
$ret_{i,t-1}$		-0.023***	-0.024***
$oib_{i,t-1}$		-0.024***	-0.023***
$diff\ pslope_{i,t-1}$			0.040***
$poibfin_{i,t-1}$			-0.013**
N	32,966	32,814	32,814
Adj R-Square	0.22%	0.34%	0.58%

Panel B: Equally-weighted portfolio inventory

Intercept	-0.010**	-0.012**	-0.011***
$invav_{i,t-1}$	0.104***	0.099***	0.096***
$EWpinvav_{i,t-1}$	0.063***	0.067***	0.068***
$ret_{i,t-1}$		-0.023***	-0.024***
$oib_{i,t-1}$		-0.024***	-0.023***
$diff\ pslope_{i,t-1}$			0.041***
$poibfin_{i,t-1}$			-0.012**
N	32,966	32,814	32,814
Adj R-Square	0.22%	0.34%	0.59%

Internet Appendix B

Table B1: Informativeness of Market Participants

This table presents analysis of informativeness of orders placed by different category of traders (as identified in the dataset) in the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India during our sample period, April to June, 2006. Order informativeness is estimated as the natural logarithm of the ratio of the quote midpoint at differen horizons after order submission (15 min, 30 min, .., 1 day) to the quote midpoint one minute before order submission multiplied by +1 (-1) for buy (sell) orders. We exclude orders that are cancelled within two minutes of submission with no execution. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	15 min	30 min	60 min	120 min	1 day
Exchange members	4.07***	4.35***	4.29***	3.81***	1.73
Individual investors	4.43***	4.79***	5.05***	4.78***	3.86***
Other instuitutions	5.33***	5.81***	6.04***	6.54***	12.10**
Financial institutions	15.82***	16.17***	17.06***	18.88***	20.41***

Table B2: Mean Reversion in Relative Inventories: 15 Minutes Intervals

This table presents results from the analysis of mean reversion in relative inventories (Panel A), relative portfolio inventories (Panel B) and relative equally-weighted portfolio inventories (Panel C) of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 15 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. $\Delta invrel_{j,i,t}$ (defined as $invrel_{j,i,t} - invrel_{j,i,t-1}$) is the dependent variable in all specifications. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta EWpinvrel_{j,t}$ (defined as $EWpinvrel_{j,t} - EWpinvrel_{j,t-1}$) is the dependent variable in all specifications. Portfolio inventory ($pinv_{j,i,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($pinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta pinvrel_{j,i,t}$ (defined as $pinvrel_{j,i,t} - pinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume), $volatility_{i,t}$ (standard deviation of 1 minute returns), $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_t$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $invrel_{j,i,t-1}$ (respectively $EWpinvrel_{j,t-1}$ or $pinvrel_{j,t-1}$) for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t}$ is a dummy variable equal to 1 when $volatility_{i,t}$ is 2 standard deviations greater than its mean. $loss_{j,t}$ is a dummy variable equal to 1 when a trader's 15-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ordinary inventory

Intercept	0.000	0.000	0.000	0.000*	0.000	0.000
$invrel_{j,i,t-1}$	-0.049***	-0.050***	-0.037***	-0.018***	-0.048***	-0.078***
$ret_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$oib_{i,t-1}$		-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
$volatility_{i,t-1}$		-0.001*	-0.001***	-0.001*	-0.001**	-0.001**
$spread_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volume_{i,t-1}$		0.001**	0.001**	0.001**	0.001**	0.002***
$invrel_{j,i,t-1} \times peak_{t-1}$			-0.031***			
$invrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.039***		
$invrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.054***	
$invrel_{j,i,t-1} \times loss_{j,t-1}$						-0.039***
N	7,074,800	6,895,500	6,895,500	6,895,500	6,895,500	6,895,500
Adj R-Square	2.50%	2.57%	2.81%	2.80%	2.68%	2.66%

Panel B: Portfolio inventory

Intercept	0.002***	0.002***	0.002***	0.003***	0.002***	0.002***
$pinvrel_{j,i,t-1}$	-0.065***	-0.066***	-0.051***	-0.041***	-0.064***	-0.061***
$ret_{i,t-1}$		0.001	0.000	0.000	0.000	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volume_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$pinvrel_{j,t-1} \times peak_{t-1}$			-0.039***			
$pinvrel_{j,t-1} \times high_{j,t-1}$				-0.069***		
$pinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.049***	
$pinvrel_{j,t-1} \times loss_{j,t-1}$						-0.055***
N	7,214,500	6,895,500	6,895,500	6,895,500	6,895,500	6,895,500
Adj R-Square	3.35%	3.42%	3.71%	4.28%	3.48%	3.60%

Panel C: Equally-weighted portfolio inventory

Intercept	0.003**	0.003**	0.003**	0.003***	0.003**	0.003**
$EWpinvrel_{j,i,t-1}$	-0.070***	-0.071***	-0.054***	-0.046***	-0.069***	-0.066***
$ret_{i,t-1}$		0.001	0.001	0.001	0.001	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.000	0.001	0.000	0.000	0.000
$volume_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$EWpinvrel_{j,i,t-1} \times peak_{t-1}$			-0.044***			
$EWpinvrel_{j,i,t-1} \times high_{j,t-1}$				-0.090***		
$EWpinvrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.051***	
$EWpinvrel_{j,i,t-1} \times loss_{j,t-1}$						-0.058***
N	7,214,500	6,895,500	6,895,500	6,895,500	6,895,500	6,895,500
Adj R-Square	3.61%	3.67%	4.01%	4.87%	3.73%	3.85%

Table B3: Mean Reversion in Relative Inventories: 60 Minutes Intervals

This table presents results from the analysis of mean reversion in relative inventories (Panel A), relative portfolio inventories (Panel B) and relative equally-weighted portfolio inventories (Panel C) of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 60 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. $\Delta invrel_{j,i,t}$ (defined as $invrel_{j,i,t} - invrel_{j,i,t-1}$) is the dependent variable in all specifications. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta EWpinvrel_{j,t}$ (defined as $EWpinvrel_{j,t} - EWpinvrel_{j,t-1}$) is the dependent variable in all specifications. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($pinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta pinvrel_{j,i,t}$ (defined as $pinvrel_{j,i,t} - pinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume), $volatility_{i,t}$ (standard deviation of 1 minute returns), $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_t$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $invrel_{j,i,t-1}$ (respectively $EWpinvrel_{j,t-1}$ or $pinvrel_{j,t-1}$) for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t}$ is a dummy variable equal to 1 when $volatility_{i,t}$ is 2 standard deviations greater than its mean. $loss_{j,t}$ is a dummy variable equal to 1 when a trader's 60-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ordinary inventory

Intercept	0.001	0.001*	0.001*	0.001*	0.001	0.001*
$invrel_{j,i,t-1}$	-0.096***	-0.097***	-0.092***	-0.035***	-0.095***	-0.095***
$ret_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$oib_{i,t-1}$		-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
$volatility_{i,t-1}$		-0.001	-0.001	-0.001	-0.001*	-0.001
$spread_{i,t-1}$		-0.002*	-0.002*	-0.002*	-0.002*	-0.002*
$volume_{i,t-1}$		0.003***	0.003***	0.003***	0.003***	0.003***
$invrel_{j,i,t-1} \times peak_{t-1}$			-0.014			
$invrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.075***		
$invrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.039	
$invrel_{j,i,t-1} \times loss_{j,t-1}$						-0.012
N	1,641,008	1,616,508	1,616,508	1,616,508	1,616,508	1,616,508
Adj R-Square	4.48%	4.54%	4.56%	4.93%	4.57%	4.55%

Panel B: Portfolio inventory

Intercept	0.003***	0.006***	0.006***	0.008***	0.006***	0.006***
$pinvrel_{j,i,t-1}$	-0.140***	-0.141***	-0.130***	-0.086***	-0.138***	-0.132***
$ret_{i,t-1}$		0.000	0.000	-0.001	0.000	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.002	0.002	0.002	0.002	0.002
$volume_{i,t-1}$		-0.002	-0.002	-0.002	-0.002	-0.002
$pinvrel_{j,i,t-1} \times peak_{t-1}$			-0.036***			
$pinvrel_{j,i,t-1} \times high_{j,t-1}$				-0.147***		
$pinvrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.060**	
$pinvrel_{j,i,t-1} \times loss_{j,t-1}$						-0.042*
N	1,641,008	1,616,508	1,616,508	1,616,508	1,616,508	1,616,508
Adj R-Square	6.61%	6.67%	6.76%	8.37%	6.71%	6.76%

Panel C: Equally-weighted Portfolio inventory

Intercept	0.006	0.005	0.005	0.007**	0.005	0.005
$EWpinvrel_{j,t-1}$	-0.152***	-0.153***	-0.142***	-0.099***	-0.150***	-0.144***
$ret_{i,t-1}$		0.000	0.000	0.000	0.000	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		0.001	0.001	0.001	0.001	0.001
$spread_{i,t-1}$		0.003**	0.003**	0.003**	0.003**	0.003**
$volume_{i,t-1}$		-0.003	-0.003	-0.003	0.000	-0.003
$EWpinvrel_{j,t-1} \times peak_{t-1}$			-0.039			
$EWpinvrel_{j,t-1} \times high_{j,t-1}$				-0.193***		
$EWpinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.068***	
$EWpinvrel_{j,t-1} \times loss_{j,t-1}$						-0.043*
N	1,641,008	1,616,508	1,616,508	1,616,508	1,616,508	1,616,508
Adj R-Square	7.16%	7.22%	7.31%	9.53%	7.27%	7.31%

Table B4: Mean Reversion in Relative Inventories: 150 Most Active Limit order Book Traders

This table presents results from the analysis of mean reversion in relative inventories (Panel A), relative portfolio inventories (Panel B) and relative equally-weighted portfolio inventories (Panel C) of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 150 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. $\Delta invrel_{j,i,t}$ (defined as $invrel_{j,i,t} - invrel_{j,i,t-1}$) is the dependent variable in all specifications. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta EWpinvrel_{j,t}$ (defined as $EWpinvrel_{j,t} - EWpinvrel_{j,t-1}$) is the dependent variable in all specifications. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($pinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta pinvrel_{j,i,t}$ (defined as $pinvrel_{j,i,t} - pinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume), $volatility_{i,t}$ (standard deviation of 1 minute returns), $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_t$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $invrel_{j,i,t-1}$ (respectively $EWpinvrel_{j,t-1}$ or $pinvrel_{j,t-1}$) for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t}$ is a dummy variable equal to 1 when $volatility_{i,t}$ is 2 standard deviations greater than its mean. $loss_{j,t}$ is a dummy variable equal to 1 when a trader's 30-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ordinary inventory

Intercept	0.001	0.000	0.000	0.000	-0.001	0.000
$invrel_{j,i,t-1}$	-0.116***	-0.112***	-0.083***	-0.030***	-0.110***	-0.104***
$ret_{i,t-1}$		0.001	0.001	0.001	0.000	0.000
$oib_{i,t-1}$		-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
$volatility_{i,t-1}$		-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
$spread_{i,t-1}$		-0.001	-0.001	-0.001	-0.001	-0.001
$volume_{i,t-1}$		0.002**	0.002***	0.002**	0.002***	0.002***
$invrel_{j,i,t-1} \times peak_{t-1}$			-0.071***			
$invrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.096***		
$invrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.067***	
$invrel_{j,i,t-1} \times loss_{j,t-1}$						-0.066***
N	5,186,567	5,069,717	5,069,717	5,069,717	5,069,717	5,069,717
Adj R-Square	5.29%	5.88%	6.45%	6.41%	5.96%	6.12%

Panel B: Portfolio inventory

Intercept	0.007***	0.007***	0.007***	0.010***	0.007***	0.007***
$pinvrel_{j,t-1}$	-0.141***	-0.143***	-0.112***	-0.082***	-0.141***	-0.130***
$ret_{i,t-1}$		0.001	0.001	0.001	0.001	-0.001
$oib_{i,t-1}$		0.000*	0.000	0.000	0.000*	0.000*
$volatility_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volume_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$pinvrel_{j,t-1} \times peak_{t-1}$			-0.084***			
$pinvrel_{j,t-1} \times high_{j,t-1}$				-0.147***		
$pinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.060***	
$pinvrel_{j,t-1} \times loss_{j,t-1}$						-0.087***
N	5,186,567	5,069,717	5,069,717	5,069,717	5,069,717	5,069,717
Adj R-Square	7.36%	7.47%	8.08%	9.40%	7.52%	7.81%

Panel C: Equally-weighted portfolio inventory

Intercept	0.008***	0.008***	0.008***	0.011***	0.008***	0.008**
$EWpinvrel_{j,t-1}$	-0.148***	-0.150***	-0.118***	-0.090***	-0.148***	-0.137***
$ret_{i,t-1}$		0.001	0.001	0.000	0.000	-0.001
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		-0.001	0.000	0.000	0.000	0.000
$spread_{i,t-1}$		0.000	0.001	0.000	0.000	0.000
$volume_{i,t-1}$		0.001	0.001	0.001	0.001	0.001
$EWpinvrel_{j,t-1} \times peak_{t-1}$			-0.090***			
$EWpinvrel_{j,t-1} \times high_{j,t-1}$				-0.178***		
$EWpinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.066***	
$EWpinvrel_{j,t-1} \times loss_{j,t-1}$						-0.093***
N	5,186,567	5,069,717	5,069,717	5,069,717	5,069,717	5,069,717
Adj R-Square	7.77%	7.87%	8.53%	10.35%	7.92%	8.24%

Table B5: Quoting Regimes and Relative Inventories: 150 Voluntary Liquidity Providers

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) different quoting regimes (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. Panel A presents results of multinomial logit regressions with three (limit order) quoting regimes: when a trader places only buy orders (*Buy Orders Only*); when a trader places only sell orders (*Sell Order Only*); and when a trader is indifferent between the two sides, either present in both or absent in both. The third regime is used as the base case to which the first two are compared. Panel B presents results of logit regressions with only two (limit order) quoting regimes: *Sell Order Only* and *Buy Orders Only*, used as the base case. All the variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	*Sell Orders Only*	-4.050***	-4.054***	-4.055***
	Buy Orders Only	-3.818***	-3.817***	-3.818***
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.113***	0.115***	0.103***
	Buy Orders Only	-0.065***	-0.066***	-0.064***
$EWpinvrel_{j,i,t-1}$	*Sell Orders Only*		0.064***	
	Buy Orders Only		-0.018***	
$pinvrel_{j,i,t-1}$	*Sell Orders Only*			0.069***
	Buy Orders Only			-0.005**
$ret_{i,t-1}$	*Sell Orders Only*	-0.005	-0.004	-0.004
	Buy Orders Only	0.026***	0.026***	0.026***
$volume_{i,t-1}$	*Sell Orders Only*	0.049***	0.049***	0.049***
	Buy Orders Only	0.072***	0.072***	0.072***
$oib_{i,t-1}$	*Sell Orders Only*	0.003	0.003	0.003
	Buy Orders Only	-0.008***	-0.008***	-0.008***
N		5,186,567	5,186,567	5,186,567
Pseudo R-Square		0.06%	0.07%	0.07%

Table B6: Trader Order Imbalances and Relative Inventories: 150 Voluntary Liquidity Providers

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) order imbalances (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $trader\ oib_{j,i,t}$, the dependent variable, is a trader's order imbalance (buy-initiated minus sell-initiated trader's total order volume, expressed as a ratio of trader's total order volume) in a given stock during a given time interval; it is standardized by trader and stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume) and $volume_{i,t}$ (trading volume) are standardized for each stock. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	-0.014**	-0.012**	-0.014***
$invrel_{j,i,t-1}$	-0.041***	-0.043***	-0.038***
$EWpinvrel_{j,i,t-1}$		-0.029***	
$pinvrel_{j,i,t-1}$			-0.024***
$trader\ oib_{j,i,t-1}$	0.129***	0.129***	0.129***
$ret_{i,t-1}$	0.007*	0.007*	0.007*
$volume_{i,t-1}$	0.011***	0.011***	0.011***
$oib_{i,t-1}$	-0.012***	-0.012***	-0.012***
N	637,539	637,539	637,539
Adj R-Square	2.50%	2.58%	2.56%

Table B7: Bid-Ask Spreads and Portfolio Inventories: 150 Voluntary Liquidity Providers

This table presents results from the analysis of Bid-Ask spreads and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $spread$ (estimated from the order book, expressed as a ratio of the mid-quote) is the dependent variable in all specifications. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader$inv_{j,i,t}$ at time t; it is standardized by stock. $EWpinvrange_{i,t}$ and $pinvrange_{i,t}$are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$are defined analogously. $volatility_{i,t}$ (standard deviation of 1 minute returns) and $volume_{i,t}$ (trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $pspread_{i,t}$ is the equal weighted average bid-ask spread of the rest of the 49 stocks in the Nifty index. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.071***	0.060**	-0.072*	-0.031***
$invrange_{i,t-1}$	-0.025**	-0.028***		
$EWpinvrange_{i,t-1}$	-0.126***			
$pinvrange_{i,t-1}$		-0.119***		
$\|invav_{i,t-1}\|$			-0.069	-0.038
$\|EWpinvav_{i.t-1}\|$			0.050*	
$\|pinvav_{i.t-1}\|$				0.048*
$volatility_{i,t-1}$	0.017**	0.017**	0.017**	-0.025***
$volume_{i,t-1}$	0.042***	0.042***	0.042***	0.034**
$open\ close_{t-1}$	0.037***	0.037***	0.040***	0.039***
$pspread_{i,t}$	0.127***	0.128***	0.129***	0.130***
N	32,908	32,908	32,908	32,908
Adj R-Square	4.96%	4.92%	4.83%	4.82%

Table B8: Portfolio Inventories and Depth and Slope of Limit Order Book: 150 Voluntary Liquidity Providers

This table presents results on the effect of Voluntary Liquidity Providers' (VLPs) inventories on depth (Panel A) and slope (Panel B) if the Limit Order Book (LOB). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $buy\ depth_{i,t}$ and $sell\ depth_{i,t}$ are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. $diff\ depth_{i,t}$, the dependent variable, is $buy\ depth_{i,t}$ minus $sell\ depth_{i,t}$ divided by the average depth; it is standardized by each stock. $buy\ slope_{i,t}$ is the ratio of the difference in the most aggressive buy-side limit order price and the 10th most aggressive buy-side limit order price and the total volume of the ten most aggressive limit orders on the buy side; $sell\ slope_{i,t}$ is defined analogously. $diff\ slope_{i,t}$, the dependent variable, is $buy\ slope_{i,t}$ minus $sell\ slope_{i,t}$ divided by the average slope; it is standardized by each stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invav_{i,t}$ is the average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $pinvav_{i,t}$ and $EWpinvav_{i,t}$ are defined analogously. $ret_{i,t}$ (total stock return) and $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume) are standardized for each stock. $diff\ pdepth_{i,t}$ is the equal weighted average $diff\ depth_{i,t}$ of the rest of the 49 stocks in the Nifty index. $diff\ pslope_{i,t}$ is the equal weighted average $diff\ slope_{i,t}$ of the rest of the 49 stocks in the Nifty index. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	Depth		*Slope*	
Intercept	0.027***	0.027***	-0.012***	-0.012***
$invav_{i,t-1}$	-0.147***	-0.140***	0.118***	0.107***
$EWpinvav_{i,t-1}$	-0.070***		0.089***	
$pinvav_{i,t-1}$		-0.068***		0.092***
$ret_{i,t-1}$	0.035***	0.035***	-0.023***	-0.023***
$oib_{i,t-1}$	0.100***	0.100***	-0.023***	-0.023***
$diff\ pdepth_{i,t}$	0.065***	0.065***		
$diff\ pslope_{i,t}$			0.041***	0.040***
N	32,814	32,814	32,966	32.814
Adj R-Square	2.71%	2.70%	0.19%	0.54%

Table B9: Idiosyncratic Volatility and Portfolio Inventories: 150 Voluntary Liquidity Providers

This table presents results from the analysis of Idiosyncratic volatility and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Idiosyncratic volatility ($ivolatility_{i,t}$), estimated as the absolute value of the residual from a market-model regression, is the dependent variable in all regressions. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$ are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$ are defined analogously. $spread_{i,t}$ (estimated from the order book, expressed as a ratio of the mid-quote) is standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.047	0.020	-0.098***	-0.098***
$invrange_{i,t-1}$	-0.084***	-0.085***		
$EWpinvrange_{i,t}$	-0.116***			
$pinvrange_{i,t}$		-0.094***		
$\|invav_{i,t-1}\|$			0.241***	0.241***
$\|EWpinvav_{i,t-1}\|$			0.001	
$\|pinvav_{i,t-1}\|$				0.003
$spread_{i,t-1}$	0.044***	0.045***	0.047***	0.047***
$open\ close_{t-1}$	0.107***	0.107***	0.108***	0.108***
$ivolatility_{i,t-1}$	0.118***	0.119***	0.119***	0.119***
$pivolatility_{i,t-1}$	0.374***	0.375***	0.380***	0.380***
N	32,596	32,596	32,596	32,596
Adj R-Square	17.17%	17.16%	17.22%	17.21%

Table B10: Pricing Errors and Portfolio Inventories: 150 Voluntary Liquidity Providers

This table presents results on effects of and Voluntary Liquidity Providers' (VLPs) portfolio inventories on price pressures. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. For each stock i we estimate the state-space model of the price series $p_{i,t} = m_{i,t} + s_{i,t}$, where the efficient price series follows a random walk with a drift $m_{i,t} = m_{i,t-1} + \beta_{im} r_t^M + w_{i,t}$ and the process for the stationary pricing error follows $s_{i,t} = \alpha_i invav_{i,t} + \delta_i pinvav_{i,t} + \beta_{is} r_t^M + u_{i,t}$. The error term $u_{i,t}$ is normally distributed and uncorrelated with $w_{i,t}$. The r_t^M term captures the adjustment to common factor innovation and is computed as the demeaned market return. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invav_{i,t}$ is the average trader $inv_{i,t}$; $pinvav_{i,t}$ is the average trader $pinv_{j,i,t}$ in a given time period; it is standardized by stock. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ is defined analogously. The dummy variable $dinv_{i,t}$ that is equal to 1 if the inventory inter-quartile range $invrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. Similarly, $dpinv_{i,t}$ is equal to 1 if the inventory inter-quartile range $pinvrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. The Table presents the averages of the estimated coefficients across 50 stocks. Two tailed p-values are also reported.

$invav_{i,t}$	-35.31***	-29.47***	-32.85***	-38.80***
$invav_{i,t} \times invrange_{i,t}$		-128.04**		
$invav_{i,t} \times (invrange_{i,t})^2$			-130.48	
$invav_{i,t} \times dinv_{i,t}$				4.00
$pinvav_{i,t}$	-7.13***	-3.27***	-15.70***	-3.54
$pinvav_{i,t} \times pinvrange_{i,t}$		16.47***		
$pinvav_{i,t} \times (pinvrange_{i,t})^2$			5.93***	
$pinvav_{i,t} \times dpinv_{i,t}$				-4.31*
$r_t^M (\beta_m)$	1.02***	1.01***	1.01***	1.01***
$r_t^M (\beta_s)$	-0.05***	-0.05***	-0.05***	-0.05***

Table B11: Extreme Price Movements (EPMs) and Portfolio Inventories: 150 Voluntary Liquidity Providers

This table presents results from the analysis of EPMs and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active LOB traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange, India - during April to June, 2006. EPMs are defined as intervals that belong to the 99.9th percentile of 1-second absolute mid-quote return for each stock. For Logit regressions, the dependent (binary) variable $extreme_{i,t}$ is equal one when a stock has experienced an EPM in a 30-minute interval. For Tobit recreations, the dependent variable $nrextreme_{i,t}$ is the number of EPMs experienced by a stock in a 30-minute interval. All the following variables are calculated over 30-minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$ are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$ is defined analogously. $volatility_{i,t}$ (standard deviation of 1 minute stock returns), $volume_{i,t}$ (trading volume), and $|oib_{i,t}|$ (absolute value of buy minus sell trading volume, expressed as a ratio of total trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. Two tailed p-values are also reported.

Panel A: Extreme Price Movements

Intercept	-3.37***	-3.37***	-7.08***	-7.01***	-3.60***	-3.71***	-7.87***	-7.77***
$invrange_{i,t-1}$	-0.81*	-0.81*			-0.96*	-0.89*		
$EWpinvrange_{i,t-1}$	-1.95***				-2.28***			
$pinvrange_{i,t-1}$		-2.02***				-2.25***		
$\|invav_{i,t-1}\|$			-1.23	-1.43**			-1.64	-1.88**
$\|EWpinvav_{i,t-1}\|$			3.78***				4.26***	
$\|pinvav_{i,t-1}\|$				3.74***				4.25***
$volatility_{i,t-1}$	0.47***	0.47***	0.42***	0.42***	0.70***	0.70***	0.62***	0.63***
$volume_{i,t-1}$	0.08*	0.08*	0.13**	0.13**	0.16**	0.16**	0.17**	0.17**
$\|oib_{i,t-1}\|$	-0.19	-0.19	-0.18	-0.18	-0.28	-0.29	-0.25	-0.24
$open\ close_{t-1}$	0.26	0.27	0.46***	0.46**	0.32	0.32	0.58***	0.57***
$extreme_{i,t-1}$	1.77***	1.76***	1.32***	1.37***				
$nrextreme_{i,t-1}$					2.48***	2.46***	1.97***	2.02***
N	32,908	32,908	32,908	32,908	32,908	32,908	32,908	32,908
Wald Test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Panel B: Transient Jumps

Intercept	-4.86***	-4.88***	-3.80***	-3.77***	-7.52***	-7.54***	-6.13***	-6.09***
$invrange_{i,t-1}$	-1.01***	-1.02***			-1.27***	-1.30***		
$EWpinvrange_{i,t-1}$	-1.28***				-1.70***			
$pinvrange_{i,t-1}$		-1.32***				-1.76***		
$\lvert invav_{i,t-1}\rvert$			-0.38	-0.41			-0.54	-0.57*
$\lvert EWpinvav_{i,t-1}\rvert$			0.80***				1.09***	
$\lvert pinvav_{i,t-1}\rvert$				0.70***				0.97***
$volatility_{i,t-1}$	0.16***	0.16***	0.11***	0.11***	0.20***	0.20***	0.14***	0.14***
$volume_{i,t-1}$	-0.01	-0.01	-0.01	-0.01	0.00	-0.00	0.00	0.00
$\lvert oib_{i,t-1}\rvert$	-0.09	-0.09	-0.10	-0.10	-0.11	-0.10	-0.12	-0.12
$open\ close_{t-1}$	0.12*	0.12*	0.09	0.09	0.20**	0.23**	0.15*	0.15*
$jump_{i,t-1}$	1.08***	1.08***	1.15***	1.15***				
$nrjump_{i,t-1}$					1.47***	1.47***	1.58***	1.57***
N	35,357	35,357	35,357	35,357	35,357	35,357	35,357	35,357
Wald Test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Table B12: Mean Reversion in Relative Inventories: 300 Most Active Limit order Book Traders

This table presents results from the analysis of mean reversion in relative inventories (Panel A), relative portfolio inventories (Panel B) and relative portfolio inventories (Panel C) of Voluntary Liquidity Provider's (VLPs). VLPs are identified as the 300 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Inventories ($inv_{j,i,t}$) are standardized by trader and stock. Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock. $\Delta invrel_{j,i,t}$ (defined as $invrel_{j,i,t} - invrel_{j,i,t-1}$) is the dependent variable in all specifications. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta EWpinvrel_{j,t}$ (defined as $EWpinvrel_{j,t} - EWpinvrel_{j,t-1}$) is the dependent variable in all specifications.Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative portfolio inventory ($pinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. $\Delta pinvrel_{j,i,t}$ (defined as $pinvrel_{j,i,t} - pinvrel_{j,i,t-1}$) is the dependent variable in all specifications. Control variables $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume), $volatility_{i,t}$ (standard deviation of 1 minute returns), $spread_{i,t}$ (bid-ask spread) and $volume_{i,t}$ (trading volume) are standardized for each stock. $peak_t$ is a dummy variable equal to 1 in the first and last hour of trading. $high_{j,i,t-1}$ is a dummy variable equal to 1 when $invrel_{j,i,t-1}$ (respectively $pinvrel_{j,t-1}$ or $einvrel_{j,t-1}$) for a trader is 2 standard deviations greater than its mean. $volat\ high_{i,t}$ is a dummy variable equal to 1 when $volatility_{i,t}$ is 2 standard deviations greater than its mean. $loss_{j,t}$ is a dummy variable equal to 1 when a trader's 30-minute aggregate revenue from all the 50 stocks in the sample is more than 2 standard deviations below its mean. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ordinary inventory

Intercept	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
$invrel_{j,i,t-1}$	-0.170***	-0.170***	-0.128***	-0.031***	-0.166***	-0.158***
$ret_{i,t-1}$		0.000	0.000	0.000	0.000	-0.001**
$oib_{i,t-1}$		-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
$volatility_{i,t-1}$		-0.001***	-0.001***	-0.001***	-0.002***	-0.002***
$spread_{i,t-1}$		-0.001	-0.001*	-0.001	-0.001	-0.001
$volume_{i,t-1}$		0.002***	0.002***	0.002***	0.002***	0.002***
$invrel_{j,i,t-1} \times peak_{t-1}$			-0.104***			
$invrel_{j,i,t-1} \times high_{j,i,t-1}$				-0.157***		
$invrel_{j,i,t-1} \times volat\ high_{i,t-1}$					-0.094***	
$invrel_{j,i,t-1} \times loss_{j,t-1}$						-0.079***
N	10,367,756	10,134,056	10,134,056	10,134,056	10,134,056	10,134,056
Adj R-Square	8.99%	8.99%	9.80%	9.78%	9.10%	9.23%

Panel B: Portfolio inventory

Intercept	0.006***	0.006***	0.006***	0.009***	0.006***	0.006***
$einvrel_{j,t-1}$	-0.191***	-0.193***	-0.154***	-0.098***	-0.192***	-0.181***
$ret_{i,t-1}$		0.000	0.000	-0.001	0.000	-0.002**
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		-0.002***	-0.002***	-0.001**	-0.002***	-0.002***
$spread_{i,t-1}$		0.002***	-0.002**	-0.002**	-0.002***	-0.002***
$volume_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$pinvrel_{j,t-1} \times peak_{t-1}$			-0.106***			
$pinvrel_{j,t-1} \times high_{j,t-1}$				-0.204***		
$pinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.036***	
$pinvrel_{j,t-1} \times loss_{j,t-1}$						-0.083***
N	10,367,756	10,134,056	10,134,056	10,134,056	10,134,056	10,134,056
Adj R-Square	10.06%	10.21%	10.92%	13.03%	10.22%	10.45%

Panel C: Equally-weighted portfolio inventory

Intercept	0.008***	0.008***	0.008***	0.010***	0.008***	0.008***
$EWpinvrel_{j,t-1}$	-0.198***	-0.200***	-0.160***	-0.105***	-0.199***	-0.186***
$ret_{i,t-1}$		0.000	0.000	-0.001	0.000	-0.002**
$oib_{i,t-1}$		0.000	0.000	0.000	0.000	0.000
$volatility_{i,t-1}$		-0.002***	-0.002***	-0.002**	-0.002***	-0.002***
$spread_{i,t-1}$		-0.002**	-0.001*	-0.002**	-0.002**	-0.002**
$volume_{i,t-1}$		0.001	0.001	0.001	0.001	0.001
$EWpinvrel_{j,t-1} \times peak_{t-1}$			-0.110***			
$EWpinvrel_{j,t-1} \times high_{j,t-1}$				-0.232***		
$EWpinvrel_{j,t-1} \times volat\ high_{i,t-1}$					-0.042***	
$EWpinvrel_{j,t-1} \times loss_{j,t-1}$						-0.094***
N	10,367,756	10,134,056	10,134,056	10,134,056	10,134,056	10,134,056
Adj R-Square	10.42%	10.56%	11.30%	14.00%	10.57%	10.86%

Table B13: Quoting Regimes and Relative Inventories: 300 Voluntary Liquidity Providers

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) different quoting regimes (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. Panel A presents results of multinomial logit regressions with three (limit order) quoting regimes: when a trader places only buy orders (*Buy Orders Only*); when a trader places only sell orders (*Sell Order Only*); and when a trader is indifferent between the two sides, either present in both or absent in both. The third regime is used as the base case to which the first two are compared. Panel B presents results of logit regressions with only two (limit order) quoting regimes: *Sell Order Only* and *Buy Orders Only*, used as the base case. All the variables are calculated over 30 minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy initiated minus sell-initiated trading volume, expressed as a ratio of total trading) and $volume_{i,t}$ (trading volume) are standardized for each stock. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	*Sell Orders Only*	-4.329***	-4.334***	-4.334***
	Buy Orders Only	-4.111***	-4.110***	-4.110*
$invrel_{j,i,t-1}$	*Sell Orders Only*	0.148***	0.149***	0.137***
	Buy Orders Only	-0.111***	-0.112***	-0.108***
$EWpinvrel_{j,i,t-1}$	*Sell Orders Only*		0.071***	
	Buy Orders Only		-0.037*	
$pinvrel_{j,i,t-1}$	*Sell Orders Only*			0.075***
	Buy Orders Only			-0.019***
$ret_{i,t-1}$	*Sell Orders Only*	0.010***	0.011**	0.011***
	Buy Orders Only	0.009***	0.009***	0.009***
$volume_{i,t-1}$	*Sell Orders Only*	0.052***	0.052***	0.052***
	Buy Orders Only	0.077***	0.077***	0.077***
$oib_{i,t-1}$	*Sell Orders Only*	0.003	0.003	0.003
	Buy Orders Only	-0.011***	-0.011***	-0.011***
N		10,367,756	10,367,756	10,367,756
Pseudo R-Square		0.10%	0.11%	0.11%

Table B14: Trader Order Imbalances and Relative Inventories: 300 Voluntary Liquidity Providers

This table presents results from the analysis of Voluntary Liquidity Providers' (VLPs) order imbalances (as observed in the limit order book) and their inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $trader\ oib_{j,i,t}$, the dependent variable, is a trader's order imbalance (buy-initiated minus sell-initiated trader's total order volume, expressed as a ratio of trader's total order volume) in a given stock during a given time interval; it is standardized by trader and stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). Relative inventory ($invrel_{j,i,t}$) is calculated as a trader's standardized inventory minus the median standardized inventory in a stock; $pinvrel_{j,i,t}$ is defined analogously. All inventory variables are standardized by trader and stock. $ret_{i,t}$ (stock return), $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume) and $volume_{i,t}$ (trading volume) are standardized for each stock. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.002	-0.016***	0.004	-0.014***	0.002	-0.016***
$invrel_{j,i,t-1}$	-0.041***	-0.040***	-0.042***	-0.041***	-0.037***	-0.036***
$EWpinvrel_{j,i,t-1}$			-0.033***	-0.036***		
$pinvrel_{j,i,t-1}$					-0.026***	-0.028***
$trader\ oib_{j,i,t-1}$		0.127***		0.128***		0.128***
$ret_{i,t-1}$		0.006*		0.006*		0.006*
$volume_{i,t-1}$		0.009***		0.009***		0.009***
$oib_{i,t-1}$		-0.012***		-0.013***		-0.013***
N	1,155,734	809,377	1,155,734	809,377	1,155,734	809,377
Adj R-Square	0.95%	2.74%	1.06%	2.87%	1.02%	2.83%

Table B15: Bid-Ask Spreads and Portfolio Inventories: 300 Voluntary Liquidity Providers

This table presents results from the analysis of Bid-Ask spreads and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $spread$ (estimated from the order book, expressed as a ratio of the mid-quote) is the dependent variable in all specifications. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Relative equally weighted portfolio inventory ($EWpinvrel_{j,i,t}$) is calculated as a trader's standardized portfolio inventory minus the median standardized portfolio inventory in a stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$ are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$ are defined analogously. $volatility_{i,t}$ (standard deviation of 1 minute returns) and $volume_{i,t}$ (trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. $pspread_{i,t}$ is the equal weighted average bid-ask spread of the rest of the 49 stocks in the Nifty index. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.075***	0.054***	-0.066***	-0.065***
$invrange_{i,t-1}$	-0.084***	-0.086***		
$EWpinvrange_{i,t-1}$	-0.138***			
$pinvrange_{i,t-1}$		-0.122***		
$\|invav_{i,t-1}\|$			-0.074	-0.074
$\|EWpinvav_{i,t-1}\|$			0.023	
$\|pinvav_{i,t-1}\|$				0.019
$volatility_{i,t-1}$	0.016**	0.016**	0.018**	0.018
$volume_{i,t-1}$	0.042***	0.042***	0.042***	0.042**
$open\ close_{t-1}$	0.036***	0.037***	0.039***	0.039***
$pspread_{i,t}$	0.127***	0.128***	0.131***	0.131***
N	32,908	32,908	32,908	32,908
Adj R-Square	4.96%	4.95%	4.80%	4.80%

Table B16: Portfolio Inventories, Depth and Slope of Limit Order Book: 300 Voluntary Liquidity Providers

This table presents results on the effect of Voluntary Liquidity Providers' (VLPs) inventories on depth (Panel A) and slope (Panel B) if the Limit Order Book (LOB). VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. $buy\ depth_{i,t}$ and $sell\ depth_{i,t}$ are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. $diff\ depth_{i,t}$, the dependent variable, is $buy\ depth_{i,t}$ minus $sell\ depth_{i,t}$ divided by the average depth; it is standardized by each stock. $buy\ slope_{i,t}$ is the ratio of the difference in the most aggressive buy-side limit order price and the 10th most aggressive buy-side limit order price and the total volume of the ten most aggressive limit orders on the buy side; $sell\ slope_{i,t}$ is defined analogously. $diff\ slope_{i,t}$, the dependent variable, is $buy\ slope_{i,t}$ minus $sell\ slope_{i,t}$ divided by the average slope; it is standardized by each stock. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983).Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. $invav_{i,t}$ is the average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $pinvav_{i,t}$ and $EWpinvav_{i,t}$are defined analogously. $ret_{i,t}$ (total stock return) and $oib_{i,t}$ (buy minus sell trading volume, expressed as a ratio of total trading volume) are standardized for each stock. $diff\ pdepth_{i,t}$ is the equal weighted average $diff\ depth_{i,t}$ of the rest of the 49 stocks in the Nifty index. $diff\ pslope_{i,t}$ is the equal weighted average $diff\ slope_{i,t}$ of the rest of the 49 stocks in the Nifty index. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	Depth		*Slope*	
Intercept	0.027***	0.027***	-0.011***	-0.012***
$invav_{i,t-1}$	-0.210***	-0.202***	0.197***	0.180***
$EWpinvav_{i,t-1}$	-0.082***		0.125***	
$pinvav_{i,t-1}$		-0.076***		0.130***
$ret_{i,t-1}$	0.035***	0.034***	-0.022***	-0.022***
$oib_{i,t-1}$	0.100***	0.100***	-0.023***	-0.023***
$diff\ pdepth_{i,t}$	0.067***	0.068***		
$diff\ pslope_{i,t}$			0.041***	0.041***
N	32,814	32,814	32,814	32.814
Adj R-Square	2.63%	2.62%	0.53%	0.53%

Table B17: Idiosyncratic Volatility and Portfolio Inventories: 300 Voluntary Liquidity Providers

This table presents results from the analysis of Idiosyncratic volatility and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. All the variables are calculated over 30 minute intervals. Idiosyncratic volatility ($ivolatility_{i,t}$), estimated as the absolute value of the residual from a market-model regression, is the dependent variable in all regressions. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$are defined analogously. $spread_{i,t}$ (estimated from the order book, expressed as a ratio of the mid-quote) is standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. Standard errors are clustered by time. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Intercept	0.087**	0.042	-0.099***	-0.100***
$invrange_{i,t-1}$	-0.127***	-0.128***		
$EWpinvrange_{i,t}$	-0.149***			
$pinvrange_{i,t}$		-0.112***		
$\|invav_{i,t-1}\|$			0.372***	0.371***
$\|EWpinvav_{i,t-1}\|$			0.012	
$\|pinvav_{i,t-1}\|$				0.020
$spread_{i,t-1}$	0.044***	0.044***	0.047***	0.046***
$open\ close_{t-1}$	0.106***	0.107***	0.108***	0.108***
$ivolatility_{i,t-1}$	0.118***	0.119***	0.119***	0.119***
$pivolatility_{i,t-1}$	0.371***	0.373***	0.380***	0.380***
N	32,596	32,596	32,596	32,596
Adj R-Square	17.18%	17.16%	17.22%	17.22%

Table B18: Pricing Error and Portfolio Inventories: 300 Voluntary Liquidity Providers

This table presents results on effects of and Voluntary Liquidity Providers' (VLPs) portfolio inventories on price pressures. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. For each stock i we estimate the state-space model of the price series $p_{i,t} = m_{i,t} + s_{i,t}$, where the efficient price series follows a random walk with a drift $m_{i,t} = m_{i,t-1} + \beta_{im} r_t^M + w_{i,t}$ and the process for the stationary pricing error follows $s_{i,t} = \alpha_i invav_{i,t} + \delta_i pinvav_{i,t} + \beta_{is} r_t^M + u_{i,t}$. The error term $u_{i,t}$ is normally distributed and uncorrelated with $w_{i,t}$. The r_t^M term captures the adjustment to common factor innovation and is computed as the demeaned market return. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invav_{i,t}$ is the average trader $inv_{i,t}$, $pinvav_{i,t}$ is the average trader $pinv_{j,i,t}$, and $EWpinvav_{i,t}$ is the average trader $EWpinv_{j,i,t}$ in a given time period; they are standardized by stock. $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$ are defined analogously. The dummy variable $dinv_{i,t}$ that is equal to 1 if the inventory inter-quartile range $invrange_{i,t}$ is 1.65 standard deviation below its mean value and 0 otherwise. $dpinv_{i,t}$ and $dEWpinv_{i,t}$ are defined analogously. The Table presents the averages of the estimated coefficients across 50 stocks. Two tailed p-values are also reported.

Panel A: Portfolio inventory

$invav_{i,t}$	-35.31***	-29.47***	-32.85***	-38.80***
$invav_{i,t} \times invrange_{i,t}$		-128.04**		
$invav_{i,t} \times (invrange_{i,t})^2$			-130.48	
$invav_{i,t} \times dinv_{i,t}$				4.00
$pinvav_{i,t}$	-7.13***	-3.27***	-15.70***	-3.54
$pinvav_{i,t} \times pinvrange_{i,t}$		16.47***		
$pinvav_{i,t} \times (pinvrange_{i,t})^2$			5.93***	
$pinvav_{i,t} \times dpinv_{i,t}$				-4.31*
$r_t^M(\beta_m)$	1.02***	1.01***	1.01***	1.01***
$r_t^M(\beta_s)$	-0.05***	-0.05***	-0.05***	-0.05***

Panel B: Equally-weighted portfolio inventory

$invav_{i,t}$	-36.09***	-30.51***	-33.81***	-39.80***
$invav_{i,t} \times invrange_{i,t}$		127.08**		
$invav_{i,t} \times (invrange_{i,t})^2$			-131.92	
$invav_{i,t} \times dinv_{i,t}$				4.22
$pinvav_{i,t}$	-4.51*	-16.60*	-10.65**	-0.23
$EWpinvav_{i,t} \times EWpinvrange_{i,t}$		10.26		
$EWpinvav_{i,t} \times (EWpinvrange_{i,t})^2$			4.30*	
$EWpinvav_{i,t} \times dEWpinv_{i,t}$				-5.14**
$r_t^M(\beta_m)$	1.01***	1.01***	1.01***	1.01***
$r_t^M(\beta_s)$	-0.05***	-0.05***	-0.05***	-0.05***

Table B19: Extreme Price Movements (EPMs) and Portfolio Inventories: 300 Voluntary Liquidity Providers

This table presents results from the analysis of EPMs and Voluntary Liquidity Providers' (VLPs) inventories. VLPs are identified as the 100 most active limit order book traders in our data - 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India - during our sample period, April to June, 2006. EPMs are defined as intervals that belong to the 99.9[th] percentile of 1-second absolute mid-quote return for each stock. For Logit regressions, the dependent (binary) variable $extreme_{i,t}$ is equal one when a stock has experienced an EPM in a 30-minute interval. For Tobit recreations, the dependent variable $nrextreme_{i,t}$ is the number of EPMs experienced by a stock in a 30-minute interval. All the following variables are calculated over 30-minute intervals. $inv_{j,i,t}$ is a trader's inventory in a given stock during a given time interval. Equally weighted portfolio inventory ($EWpinv_{j,i,t}$) is a sum of trader's inventory positions in all stocks and are standardized by trader and stock. Portfolio inventory ($pinv_{j,t}$) is a trader's inventory in that stock ($inv_{j,i,t}$) corrected for his inventory positions in all other stocks with correlated returns calculated as per Ho and Stoll (1983). $invrange_{i,t}$ is a measure of inventory dispersion, defined as the interquartile range of trader $inv_{j,i,t}$ at time t; it is standardized by stock. $pinvrange_{i,t}$ and $EWpinvrange_{i,t}$ are defined analogously. $|invav_{i,t}|$ is the absolute value of average trader $inv_{i,t}$ in a given time period; it is standardized by stock. $|pinvav_{i,t}|$ and $|EWpinvav_{i,t}|$ are defined analogously. $volatility_{i,t}$ (standard deviation of t minute stock returns), $volume_{i,t}$ (trading volume), and $|oib_{i,t}|$ (absolute value of buy minus sell trading volume, expressed as a ratio of total trading volume) are standardized by stock. $open\ close_t$ is a dummy variable equal to 1 during first and last hour of trading. Two tailed p-values are also reported.

Panel A: Extreme price movements

Intercept	-2.97***	-3.07***	-6.66***	-6.74***	-3.29***	-3.31***	-7.44***	-7.32***
$invrange_{i,t-1}$	-1.20*	-1.14*			-1.51	-1.43		
$EWpinvrange_{i,t-1}$	-2.46***				-2.67***			
$pinvrange_{i,t-1}$		-2.42***				-2.71***		
$\lvert invav_{i,t-1}\rvert$			-2.68**	-2.46**			-3.24**	-3.53**
$\lvert EWpinvav_{i,t-1}\rvert$			4.50***				5.33***	
$\lvert pinvav_{i,t-1}\rvert$				4.68***				5.13***
$volatility_{i,t-1}$	0.47***	0.47***	0.45***	0.44***	0.70***	0.70***	0.66***	0.66***
$volume_{i,t-1}$	0.08*	0.08*	0.13**	0.13**	0.16**	0.16**	0.17**	0.18**
$\lvert oib_{i,t-1}\rvert$	-0.18	-0.19	-0.17	-0.18	-0.29	-0.29	-0.25	-0.25
$open\ close_{t-1}$	0.22	0.23	0.40**	0.40**	-0.27	-0.28	-0.51**	-0.50**
$extreme_{i,t-1}$	1.85***	1.84***	1.54***	1.49***				
$nrextreme_{i,t-1}$					-2.57***	-2.57***	-2.19***	-2.24***
N	35,670	35,670	35.670	35,670	35.670	35,670	35.670	35,670
Wald Test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Panel B: Transient jumps

Intercept	-5.40***	-5.16***	-3.65***	-3.69***	-8.24***	-7.92***	-7.32***	-7.44***
$invrange_{i,t-1}$	-2.27***	-2.28***			-2.81***	-2.83***		
$EWpinvrange_{i,t-1}$	-1.80***				-2.43***			
$pinvrange_{i,t-1}$		-1.62***				-2.19***		
$\lvert invav_{i,t-1} \rvert$			-0.79	-0.77			-3.53**	-3.24**
$\lvert EWpinvav_{i,t-1} \rvert$			0.59**				5.13***	
$\lvert pinvav_{i,t-1} \rvert$				0.73***				5.33***
$volatility_{i,t-1}$	0.17***	0.17***	0.12***	0.12***	0.22***	0.21***	0.66***	0.66***
$volume_{i,t-1}$	-0.02	0.02	-0.01	-0.01	-0.01	-0.01	0.18**	0.17**
$\lvert oib_{i,t-1} \rvert$	-0.08	-0.07	-0.10	-0.10	-0.09	-0.09	-0.25	-0.25
$open\ close_{t-1}$	0.15**	0.14**	0.07	0.07	0.25***	-0.23***	-0.50**	-0.51**
$jump_{i,t-1}$	1.03***	1.03***	1.14***	1.14***				
$nrjump_{i,t-1}$					1.38***	1.39***	-2.24***	-2.19***
N	35,670	35,670	35.670	35,670	35.670	35,670	35.670	35,670
Wald Test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01