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Trader Positions and Marketwide Liquidity Demand

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ABSTRACT

In electronic, liquid markets, traders frequently change their positions. The distribution of these trader position changes carries important information about liquidity demand in the market. From this distribution of trader position-changes, we construct a marketwide measure for intraday liquidity demand that does not necessarily depend on aggressive trading. Using a rich regulatory dataset on S&P 500 E-mini futures and 10-year Treasury futures markets, we show that this liquidity demand measure has a positive impact on prices. We then decompose our measure of liquidity demand into three components: aggressive, passive and mixed liquidity demand. Passive liquidity demand also has an impact on prices; a one standard deviation increase in passive liquidity demand is associated with 0.5 tick rise in prices for S&P 500 E-mini futures. In addition, we find that new information is incorporated into the prices when passive liquidity demanders take positions. By providing direct evidence, we contribute to the growing literature on the impact of passive limit orders.

JEL classification: G10, G130, G140.

Keywords: Liquidity, Passive Trading, Price Impact.

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I. Introduction

One objective of financial markets is to facilitate risk transfer between market participants. The party that initiates risk transfer is deemed the liquidity demander, and its counterparty is deemed as the liquidity supplier. Empirically, liquidity demanders are often identified as the side of trades that use marketable orders. However, given recent advances in financial markets, there are various reasons to challenge this definition.

Electronification of financial markets has made the determination of liquidity demanders more complicated for two reasons. First, high frequency traders have increased the amount of intraday intermediation in financial markets. As opposed to traditional market makers who provide immediacy, these new types of intraday intermediaries can demand immediacy as part of their intraday intermediation role. Indeed, they take the aggressive side of the trade about half of the time, contributing to aggressive trading, but they do not take on large positions (Kirilenko et al., 2017). As a result, it is not clear whether a measure of aggressive imbalance, such as the difference between aggressive buy and sell volume, can accurately capture which side of the trade is taking position in the market. Second, following the increasing use of electronic limit order books, where every trader can submit limit orders, it has been recognized that informed traders strategically use passive limit orders to take positions (Collin-Dufresne and Fos, 2015; Easley, de Prado and O'Hara, 2016) . In fact, Easley, de Prado and O'Hara (2016) point out that informed traders cannot simply be equated to traders who use marketable orders as they change positions. Therefore, the imbalance of aggressive buy and sell trades (e.g. order flow) may not be a precise indicator of underlying information, especially after the electronification of financial markets.

In this paper, we introduce a new measure for marketwide liquidity demand based on information present in trader positions regardless of their aggressiveness. It is important to note that liquidity demand, which is expressed by trader positions, does not necessarily coincide with demand for immediacy, as the passive side of transactions can also be demanding liquidity if passive transactions are used for taking large positions. In fact, traders often recognize a trade-off between demanding immediacy and getting a favorable execution price. Imagine a trader with long-lived information who decides to take a sizable position in an electronic limit order market. He does not need immediacy and patiently uses passive orders to reduce his transaction cost by taking the other side of immediacy demanding traders. When this trader tries to achieve his trading objective, he is likely to trade against a number of counterparties, who will experience smaller changes in their net positions.

This scenario is important for two reasons. First, this patient position taker demands liquidity but not immediacy. Traders on the aggressive side of the trades are satisfying his liquidity demand. Second, because the passive side of the transactions is fulfilled by this informed trader, it is his passive positioning that brings information to the market. Overall, this scenario highlights the difference between liquidity demand, which is generated by traders desire to build positions, and immediacy demand, which is mainly generated by traders' patience.

Our measure, which is aimed at capturing net liquidity demand in the market, is the skewness of intraday position changes across market participants. Intuitively, the skewness measure captures the imbalance between traders with large positions, who demand liquidity, and traders with small positions, who supply liquidity. It is important to note that this measure is based on position information rather than on trade information because traders can reach their desired position by several trade executions to minimize transaction costs (Bertsimas and Lo, 1998). This characterization of trading is especially true for limit order book markets, because the increased electronification of such markets has also facilitated order splitting, causing a majority of trades to be clustered at small sizes (Chordia, Roll and Subrahmanyam, 2011; Kyle, Obizhaeva and Tuzun, 2016; O'hara, Yao and Ye, 2014). With the clustered trade sizes, individual trades contain little information about trader positions. As a result, trader positions rather than transactions could better capture the true liquidity demand in the market.

We have two main findings. First, our skewness measure has impact on prices even after controlling for the demand for immediacy, as captured by the imbalance between aggressive buy and sell trades. Using trade execution information, we decompose this measure into three components: passive, aggressive, and mixed terms. This decomposition allows us to examine the differential impact of passive and aggressive positioning. We find that passive positioning has impact on prices. Second, we also show that this passive positioning incorporates information into prices and reduces market liquidity. This finding is consistent with theories of adverse selection (e.g. Glosten and Milgrom (1985) in the sense that when immediacy providers are taking positions, the market becomes less liquid, allowing them to compensate their counterparties. It is well established that immediacy demanders pay a premium when they trade (e.g. Grossman and Miller (1988)). Our results suggest that immediacy providers also pay a premium if they are taking positions.

The rest of the paper is organized as follows. Section 2 describes the literature. Section 3 introduces a simple model to illustrate our intuition for the new measure of intraday liquidity demand. Section 4 introduces data and the measures we construct. Section 5 presents analysis and findings, and Section 6 concludes.

II. Literature

Researchers have recognized that aggressive trading may not equate to liquidity demand and, hence, passive trading may not equate to liquidity supply. Menkveld (2015) highlights the need for a better measure of liquidity supply and demand that does not condition on immediacy. Biais, Declerck and Moinas (2016) argue that proprietary traders can provide liquidity even if they are aggressively trading.

The closest paper to ours is Easley, de Prado and O'Hara (2016). They develop a bulk volume trade classification and show that this measure can detect informational trading better than order flow. Our measure of liquidity demand differs from theirs in that ours captures the position build-up of large traders on one side of the market without taking signal from price changes. Instead, we study the effect of our measure on prices. But, consistent with their results, we also find that passive trading lowers market liquidity, suggesting that passive orders carry information.

Bloomfield, O'Hara and Saar (2005) use an experimental design to argue that informed traders use both market and limit orders to fully capitalize on their information. Collin-Dufresne and Fos (2015) show that activist investors, who arguably have private information prefer to use limit orders to trade patiently. These patient activist traders inherently demand liquidity but do not demand immediacy. Hence, it may not be possible to quantify the effect of informed patient traders by only analyzing the immediacy demand in the market. We contribute to this line of research by showing that traders can also affect prices when they build positions through immediacy provision without aggressively trading.

Researchers often proxy for liquidity demand in limit order markets with immediacy demand, determined by classifying trades using the Lee and Ready (1991) algorithm. Hasbrouck (1991*a*,*b*) analyze the price impact and information content of immediacy demanding trades. Chordia, Roll and Subrahmanyam (2002) study the relationship among aggressive trading, market returns and liquidity. They show that daily order flow affects market returns. Sarkar and Schwartz (2009) introduce a measure of correlation between the numbers of buyer- and seller-initiated trades, which they call market sidedness. They show that this measure is an indication of disagreements and can predict more volatility and lower bid-ask spreads. On the other hand, Hautsch and Huang (2012) estimate the price impact of incoming passive orders. Our approach mainly differs from theirs in that our estimation focuses on the impact of position build-up through executed passive orders.

Our skewness measure is naturally related to the literature on the distributional properties of trader positions. Kyle and Obizhaeva (2017) develop a framework where the distribution of positions, along with transaction costs, market resiliency, and pricing accuracy, is shown to be constant across stocks when measured per unit of business time. Andersen et al. (2015) extend this idea to intraday dynamics of number of trades, trade size and trading volume in the S&P 500 E-mini futures market. More recently, Duffie and Zhu (2017) show that allowing a mechanism through which investors can trade large quantities at a price that is not affected by their price pressure improves allocative efficiency.

III. Trader Positions and Liquidity Demand

To illustrate how our measure of liquidity demand relates to the higher moments of trader position distribution, specifically the skewness, we introduce a simple model of trading.

Assume that there is a risky asset with zero net supply and that there are two types of traders: noise traders and liquidity providers. [1] There are N risk averse liquidity providers with a profit function defined as follows.

$$\Pi(X_i) = X_i(V - P_1) - \delta X_i^{\gamma+1}$$

[1] For simplicity, we are not modelling an informed trader. However, the main results of this model still hold if an informed trader is added.

The profit of liquidity providers is a function of the size of position they take, X, the price at which price they can liquidate their position, P_1, and the fundamental value of the asset V. If the price of the asset at its expected fair value at time t=0 ($E(V) = P_0$), then $-X_i \Delta P$ is the expected revenue from providing liquidity. Assume γ is a positive odd number, then $\Pi(.)$ is a concave function. It is costly to provide liquidity for the risky asset and $\delta X_i^{\gamma+1}$ is the cost of accepting risk. The demand function of liquidity providers can be obtained from their profit function.

$$\Pi'(X_i) = -\Delta P - \delta(\gamma + 1)X_i^{\gamma} = 0 \tag{1}$$

$$\Delta P = -\delta(\gamma + 1)X_i^{\gamma} \tag{2}$$

$$X_i = -(\frac{\Delta P}{\delta(\gamma + 1)})^{\frac{1}{\gamma}} \tag{3}$$

Summing across all liquidity providers, we get

$$\Delta P = -\frac{\delta(\gamma + 1)}{N} \sum_{i=1}^{N} X_i^{\gamma} \tag{4}$$

A noise trader receives a shock to trade Y units of the risky asset and demand liquidity. Then, the market clearing condition suggests that the sum of all positions in the market is zero.

$$Y + \sum_{i=1}^{N} X_i = 0 \tag{5}$$

Substituting (3) into the market clearing condition, we obtain the relationship between Y and ΔP.

$$\Delta P = (\gamma + 1)\delta(\frac{Y}{N})^{\gamma} \tag{6}$$

Equation (4) shows the relationship between liquidity providers and price while equation (6) shows the relationship between the liquidity demanding noise trader and the price. In electronic limit order books where everyone can submit limit orders, it may not be possible to distinguish traders who demand liquidity from traders who respond to this liquidity demand. Hence, price equations (4) and (6) cannot be estimated without identification assumptions about the trading behavior of liquidity demanders and suppliers. Traditionally, traders on the passive (immediacy-providing) side of trades are assumed to be liquidity providers. We propose a specification that does not rely on immediacy demand to identify liquidity providers and demanders. This specification can be obtained by multiplying (4) by $-(\frac{1}{N})^{\gamma-1}$ and summing with equation (6).

$$\Delta P = \frac{(\gamma + 1)\delta}{(N^{\gamma-1} - N)}[Y^{\gamma} + \sum_{i=1}^{N} X_i^{\gamma}] \tag{7}$$

$[Y^{\gamma} + \sum_{i=1}^{N} X_i^{\gamma}]$ is the sum of γth power of all trader position changes.

To illustrate the intuition of this equation, imagine that 100 traders each buy one contract each and 100 traders each sell one contract. In this scenario, exactly 100 contracts exchange hands. Imagine a different situation where 1 trader buys 100 contracts and 100 traders each sell 1 contract, selling a total of 100 contracts. Because exactly 100 contracts again exchanged hands, the amount of position change in both situations is the same. However, the side that trades more than the average quantity in absolute terms demands liquidity, hence liquidity demand is balanced between buyers and sellers in the first situation while a buyer is demanding liquidity in the second situation. The skewness (γ= 3) of intraday position changes can capture the differences between these situations; it is zero in the first situation and positive in the second situation.

Importantly, the skewness of intraday trader positions does not use a measure of aggressiveness and, therefore, does not depend on immediacy demand. It is also important to note that liquidity providers each take smaller positions than their large counterparties, so the number of liquidity providers is always higher than the number of liquidity demanders. Because liquidity suppliers trade against price movements, this intuition suggests that prices should move in the opposite direction of the higher number of traders. For example, if the number of sellers is higher than the number of buyers, the price will increase.

IV. Data and Measures Used

We use intraday audit-trail transaction level data of E-mini S&P 500 and 10-year Treasury futures markets. The contracts are settled at expiration dates in March, June, September, and December of each year. The contract with the nearest expiration date, which attracts the majority of trading activity, is called the front-month contract. Our sample is from January 2015 to August 2016 and includes detailed account-level data from the U.S. Commodity Futures Trading Commission on all front-month transactions. The data set contains information about counterparties, whether the trade was buyer- or seller-initiated, the trade size (in terms of contracts), and prices, as well as time-stamps indicating transaction time stamps to the millisecond.

Individual position changes have information on the amount of liquidity demanded and supplied in the market. For one-minute intervals, we aggregate total buy and sell volume for each trader to calculate their net position changes. In our analysis, we use the distributional properties of position changes at one-minute intervals. We choose one-minute intervals for two reasons.[2]. First, we would like to show that position changes

[2]In unreported results, we repeat our analysis with 5-minute and 10-minute intervals. The results

affect prices at very high frequencies. However, at the highest frequency, event time, the skewness measure cannot be calculated because for each transaction, the skewness of the position change distribution is mechanically zero. Second, we would like to calculate our skewness measure at frequencies comparable to investment horizons of intraday intermediaries. Kirilenko et al. (2017) show that market makers and high-frequency traders liquidate half of their positions within about three and two minutes, respectively. Hence, one-minute intervals should include position changes of traders who demand and supply liquidity intraday.

Figure 1 shows the distribution of one-minute position changes observed in these two markets for the entire sample. Because position changes tend to cluster around zero, we partition the distribution into two parts: (1) position changes between -10 and 10 contracts, and (2) position changes greater than 10 contracts and less than -10 contracts. The charts on the left plot the position changes between -10 and 10 contracts. There are no zero position changes, as we do not include traders who do not change their positions within one minute even if they trade during that time frame. For the S&P 500 E-mini futures, position changes at 1 and -1 contracts each account for about 20% of the position changes. Hence, about 40% of all position changes are 1 contracts in this market. For the 10-year Treasury futures, position changes at 1 and -1 contracts are each 9% of the position changes distribution, about half of their respective shares in the S&P 500 E-mini futures. The charts on the right plot the position changes of greater than 10 contracts and fewer than -10 contracts. In both markets, the frequencies of large positive and negative position changes decay monotonically with spikes in even contracts such as 20, 25, 50, 60, 75, and 100. Some portion of the spike in 100 contracts is due to the fact that for the purpose of illustration, we mark the position changes greater than 100 contracts to 100 contracts and the position changes less than -100 contracts to -100 contracts.

are qualitatively identical.

The position change distributions in both markets appear to be symmetric during our sample period. The mean of the distribution of position changes is always zero, as the sum of all position changes is zero. Therefore, it is straightforward to calculate higher moments of this distribution.

Figure 2 explores the relationship of skewness, computed for one-minute intervals, with various measures of market activity. In addition to skewness, we compute the number of traders, total volume, price volatility (defined as the maximum observed price minus the minimum observed price), and price change (defined as the end price minus the start price). Our skewness measure is the Fisher-Pearson skewness coefficient of the trader position change distribution.[3] The price changes are calculated in number of ticks.[4] The order flow is the difference of buyer- and seller- initiated volume measured in 1,000 contracts. We split the sample of intervals into 10 groups based on our skewness value, where the first group indicates a skewness value between 1 and 0.80, the second indicates a skewness value between 0.80 and 0.60, and so on. The first row shows the average number of short traders (red) and long traders (blue) by skewness group. Price changes increase monotonically from the smallest skewness group to the largest. As skewness increases, the number of long traders decreases and the number of short traders increases. Consistent with our intuition in the previous section, this relationship suggests that price changes are negatively correlated with the number of long traders and positively correlated with the number of short traders.

Average volume and price volatility show a similar pattern: They are largest at the extreme skewness groups (groups 1 and 10), with large averages also observed in the lowest skewness groups (groups 5 and 6). The price changes are higher for higher

[3]In unreported results, in addition to skewness, we add other odd moments of the positions change distribution. Among the odd moments, skewness measure has the highest explanatory power for prices.

[4]The tick size is 0.25 index points in the E-mini S&P 500 contract and 1/64 in the 10-year Treasury futures contract.

skewness groups. Prices increase (decrease) the most for the most positively (negatively) skewed intervals.

Table I summarizes the statistics for price changes, order flow, and the skewness measure in the E-mini market. The mean and median of these variables are slightly negative, but very close to zero. A mean value of zero skewness suggests that, on average, the net marketwide liquidity demand is zero and traders take comparable short and long positions consistent with our results in Figure 1. The standard deviation of minute-by- minute price changes is about 3 ticks. The standard deviations of order flow and skewness are 0.79 and 4.43, respectively. The correlations of skewness with price changes and order flow are 0.31 and 0.41, respectively.

Table II reports the same statistics for the 10-year Treasury futures. Similarly, the mean and median of price change, order flow, and skewness are very close to zero, but their standard deviations suggest that albeit small, there is variation in these variables. Once again, skewness is highly correlated with price changes and order flow. Although skewness is highly correlated with order flow, it is important to analyze whether and how much additional effect skewness has on price changes.

V. Analysis and Findings

In this section, we analyze the relationship between the price changes and the marketwide liquidity demand captured by the skewness of the distribution of intraday position changes. The skewness measure captures the asymmetry in the sizes of short and long position changes, and this measure has a large value when few traders in the market have relatively large position changes. It is well-documented that trades that are aggressive and that therefore demand immediacy have impact on prices.[5] Our skewness

[5] Hasbrouck (1991*b*), Chordia, Roll and Subrahmanyam (2002), and others document the impact of aggressive transactions on prices.

measure is different than order flow because it measures the amount of position build-up regardless of its immediacy.

Aggresssive trades cannot completely capture liquidity demand for three reasons. First, traders split their orders to avoid detection. Order shredding makes trade size an inaccurate measure of the intended position changes of traders. Second, with increased electronification, there is significant volume related to intermediation. In other words, intermediaries trade large volumes but do not take significant positions. Third, in electronic limit order markets, traders can use a mixture of passive and aggressive orders to trade and build their intraday positions. For example, in Figure 3, we show that large traders are not always aggressive traders. This figure plots the aggressiveness ratios for one-minute position changes averaged across days. The box plots in Figure 3 show the maximum, 75th percentile, median, 25th percentile and minimum of this average aggressiveness ratio for various levels of position changes. Once again, we divide the position changes into two groups. The box plots on the left show the absolute position changes of 1 through 1000 rounded by 25. The box plots on the right show the absolute position changes of 1000 through 5000 rounded by 100. For the S&P 500 E-mini futures, the median value of average aggressiveness is less than 40% for the smallest position change group, 25 contracts. This value increases to over 70% for 400 contracts, but starts to decline for larger position changes in the box plot to the right. For example, position changes of greater than 4000 contracts generally have less than a 60% aggressiveness ratio. Similarly, for the 10-year Treasury futures contract, the median aggressiveness ratio increases initially but starts declining after 2000 contracts. The median aggressiveness ratio for position changes over 2000 contracts are generally below 40%. The aggressiveness ratios presented especially for the very large position changes are far below 1, suggesting that traders take positions with a mixture of aggressive and passive orders, which motivates a deeper investigation into the impact of aggressive and passive position changes on prices and market liquidity.

A. Sorting Returns

We start our analysis with a two-way sorting of returns. We create eight buckets for order flow and eight buckets for our skewness measure. In terms of bucket numberings, +4 (−4) represents the most positive (negative) order flow or skewness bucket. For the S&P 500 E-mini and 10-year Treasury futures markets, we report a total of 64 bucket combinations for which we measure price changes. Tables III and IV show how each bucket combinations is related to price changes. Table III presents the statistics associated with S&P 500 E-mini futures and Table IV presents the ones associated with 10-year Treasury futures.

As shown in Table III, within each order flow bucket, price changes in the S&P 500 E-mini futures are increasing as skewness goes from its lowest bucket to its highest. In other words, a higher measure of skewness is associated with higher price change for a given amount of order flow. The tests in the two rightmost columns show the difference in price change levels between the lowest and the highest skewness buckets (+4 and -4), for each order flow bucket. For the S&P 500 E-mini futures market, the difference in price change of these buckets varies between 1.06 and 2.29 ticks. The t-statistics associated with each difference measure shows that all are statistically significant.

Similarly, price changes of 10-year Treasury futures in Table IV are increasing as skewness increases within each order flow group. The difference between the largest and smallest skewness buckets varies between 0.13 and 0.54 ticks. While these differences are smaller than those in E-mini, t- statistics indicate that they are all statistically significant. In addition, given that standard deviation of price changes is significantly bigger for E-mini futures than 10-year Treasury futures, it is natural to expect smaller price changes for 10-year Treasury futures.

B. Liquidity Demand and Prices

We present analysis of OLS regression results in this section. We regress price changes measured in number of ticks, on order flow and our measure of liquidity demand- skewness of position change distribution.

$$\frac{\triangle P_t}{TickSize} = \alpha + \lambda OF_t + \beta Skew_t + \varepsilon_t \tag{8}$$

Table V summarizes the results from the regression above. We run the regression separately for S&P 500 E-mini futures and 10-year Treasury futures. First, we show univariate regressions with skewness as the only explanatory power and then add order flow to the regression to control for the demand for immediacy. When prices are regressed on skewness alone, the coefficients on the skewness measure are statistically significant with 0.27 ticks for the S&P 500 E-mini futures and 0.11 ticks for the 10-year Treasury futures. When the order flow variable is included in these regressions, the magnitudes of these coefficients decrease to 0.1 for the S&P 500 E-mini futures but increase to 0.6 for the 10-year Treasury futures. They continue to be statistically significant.

These results are also economically significant. A one standard deviation increase in the skewness measure increases prices 0.44 ticks in the S&P 500 E-mini futures and 0.12 ticks in the 10-year Treasury futures market. These results suggest that our liquidity demand measure has an impact on prices even after controlling for the demand for immediacy.

C. Components of Liquidity Demand

Summary statistics and the regression results suggest that order flow and skewness measures are correlated. In this subsection, we decompose our skewness measure into three components to isolate the component of our liquidity demand that does not demand immediacy. The position change of each trader can be separated into aggressive and passive position changes.

$$X_i = X_{i,Agg} + X_{i,Pass} \tag{9}$$

Hence, the third moment of the position change distribution can be written as a function of aggressive and passive position changes.

$$\sum_{i=1}^{n}(X_{i,Agg} + X_{i,Pass})^3 = \sum_{i=1}^{n} X_{i,Agg}^3 + \sum_{i=1}^{n} X_{i,Pass}^3 + 3\sum_{i=1}^{n} X_{i,Agg}X_{i,Pass}(X_{i,Agg} + X_{i,Pass}) \tag{10}$$

The first component is the liquidity demand with only aggressive trading. The second is the liquidity demand with only passive trading. The third is the liquidity demand with a mix of aggressive and passive trading. These components represent the extent to which trader positions are built through passive versus aggressive trading. After we decompose our skewness measure, we run the following regression

$$\frac{\triangle P_t}{TickSize} = \alpha + \lambda OF_t + \beta_1 Skew_t^{Agg} + \beta_2 Skew_t^{Pass} + \beta_3 Skew_t^{Mixed} + \varepsilon_t \tag{11}$$

The results are displayed in Table VI. We first regress the price changes on the three components of skewness. For the S&P 500 E-mini futures, the coefficients of the passive, aggressive and mixed components are 0.23, -0.05, and 0.16, respectively. These coefficients are all statistically significant. The negative coefficient on the passive skewness could appear counter intuitive at first. However, traders who take positions by trading passively necessitates order flow trading against their orders in the book. The passive skewness is likely capturing the inverse of immediacy demand if it is included in the regression without the order flow variable. To address this issue, we include order flow variable in the regression. When order flow is included in the regression, the coefficient on the passive skewness increases to 0.1 and the coefficient on the aggressive skewness decreases to 0.05. Similarly, when order flow is included in the regression for the 10-year Treasury futures, the coefficient on the passive skewness increases from -0.04 to 0.01, and the coefficient on the aggressive skewness decreases from 0.08 to 0.03.

These results have interesting interpretations for aggressive and passive trading. First, order flow can mostly capture the information in the aggressive liquidity demand. Second, the passive skewness measure has a positive impact on prices after controlling for order flow. This positive impact suggests that for a given level of order flow, passive traders pay a premium to trade against the incoming order flow. This price premium suggests that passive traders demand liquidity if they are building positions. Third, a one standard deviation increase in passive skewness increases prices 0.54 ticks in the S&P 500 E-mini futures, 18% of one-minute price volatility. Yet, one standard deviation increase in the passive skewness measure increases prices 0.03 ticks in the 10-year futures, 3% of one-minute price volatility. The effect of passive skewness appears to be smaller for the 10-year Treasury futures, but it is still economically important.

D. Information in Passive Trading

We design a structural vector auto-regression (SVAR) to assess whether the components of the skewness measure contribute to price discovery. This SVAR specification is related to the recent extensions of Hasbrouck (1991*b*) in Fleming and Mizrach (2009), and in

Brogaard, Hendershott and Riordan (2015). While these studies estimate their model in event time, our data are in one-minute frequency. In our setting, order flow and skewness measures are allowed to affect prices for up to 10 minutes.

$$Y_t = \begin{bmatrix} \Delta P_t \\ OF_t \\ Skew_t^{Agg} \\ Skew_t^{Pass} \\ Skew_t^{Mixed} \end{bmatrix} \tag{12}$$

$$\begin{bmatrix} 1 & -\beta & -\delta & -\gamma & -\theta \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} Y_t = \alpha + \sum_{i=1}^{10} \lambda_i Y_{t-i} + \epsilon_t \tag{13}$$

For brevity, we only report the impulse response function results of prices. The cumulative impulse response function of prices in response to a one standard deviation shock is plotted in the Figure 4. As expected, order flow has a large and permanent impact on prices. A one standard deviation shock to order flow increases prices by about 2 ticks in the S&P 500 E- mini futures and 0.5 ticks in the 10-year Treasury futures. Consistent with our results in the previous subsection, we find that passive skewness has a positive impact on prices. Our measure of passive skewness has a permanent price impact of 0.5 ticks in the S&P 500 E-mini futures and 0.05 ticks in the 10-year Treasury futures. The impact of mixed skewness on prices is slightly lower but also permanent. If traders who have long-lived information use passive orders to build their positions, their information may not be fully incorporated into prices within minutes. The patience of passive traders might help explain why the effects of passive and mixed skewness on prices are smaller than the order flow effect.

E. Impact on Market Liquidity

In this subsection, we analyze the effect of our skewness measure on market liquidity. Classical theories of market liquidity suggest that market liquidity deteriorates in the presence of informed trading (Glosten and Milgrom, 1985; Kyle, 1985). In general, liquidity providers make the market less liquid to compensate themselves for trading against informed traders. If the traders are building positions for informational reasons, then we expect our skewness measure to decrease market liquidity.

Measuring changes in market liquidity is difficult, however, as one has to separate out the changes in the market liquidity due to volatility. Furthermore, in deep markets such as the E-mini S&P Futures and 10-year Treasury markets, the effective spread is often one tick regardless of changes in the depth of the limit order book. Following Easley, de Prado and O'Hara (2016), we use the high-low spread estimator of Corwin and Schultz (2012), which filters out the spread component due to market volatility. This procedure allows us to concentrate on the spread component that relates to market liquidity.

Table VII summarizes the sample statistics of the Corwin-Schultz spread estimator for one minute intervals for the S&P 500 E-mini futures and the 10-year Treasury futures markets. For both markets, this spread estimator shows considerable variation. While 5th and 25th percentiles of the spread are zero, the 75th and 95th percentiles go from 2.37 basis points to 4.9 basis points for the E-mini, and from 1.2 basis points to 1.81 basis points for the 10-year Treasury futures.

The effect of the skewness measure on the spread estimator shows the impact of position imbalance on market liquidity. To investigate this relationship, we regress the Corwin-Schultz spread estimator on the absolute value of the skewness measure and the absolute value of the order flow.

Table VIII reports the results of this regression. The coefficient on the order flow is -0.34 for the E-mini and -0.05 for the 10-year Treasury futures. These coefficients are both statistically significant. In contrast, the coefficient on the skewness measure in the E-mini is 0.01 and statistically significant while it is statistically indistinguishable from zero in the 10-year Treasury Futures. The negative coefficient on the order flow could suggest that aggressive order flow could come from uninformed traders, consistent with the findings of Easley, de Prado and O'Hara (2016). When we decompose the skewness measure into its components, the coefficients of the aggressive, passive, and mixed skewness measures are 0.005, 0.03, and 0.02, respectively, and statistically significant for the E-mini. For the 10-year Treasury, the coefficient on the passive skewness measure is 0.003 and is statistically significant.

Hence, in both markets, building positions with passive orders decreases market liquidity. Passive liquidity demand impacts market liquidity, as predicted by the classical theories of market liquidity. Furthermore, in the E-mini, the coefficients on the aggressive and mixed skewness are positive and significant, suggesting that position build-up by both aggressive and mixed orders also lowers market liquidity.

VI. Conclusion

The electronification of financial markets has led to a number of important changes in the way trading takes place. First, in electronic limit order books, every trader can easily submit passive limit orders and provide immediacy while still following his long-term investment strategy. Second, traders are increasingly relying on order shredding, which leads to smaller and clustered trade sizes. Traders following this behavior leave little evidence in transactions data when they build their positions. Third, with the rise of algorithmic trading, there has been a longer chain of intermediation between buyers and sellers, resulting in higher trading volume. As opposed to traditional market makers who provide immediacy, new types of intraday intermediaries often demand immediacy but keep negligible positions. These developments make immediacy demand an imperfect measure for position accumulation by traders or their liquidity demand.

Our measure of intraday liquidity demand, skewness of the intraday trader position change distribution, is aimed at capturing large position changes in the cross-section of traders without conditioning on their immediacy demand. Traders use a mixture of aggressive and passive trades to achieve their desired positions. Our skewness measure makes it possible to separately quantify the effects of passive and aggressive trading on prices separately. We find that passive trading has an impact on prices when it is used to build positions in the market. This positioning also incorporates information into prices and makes the market less liquid.

Our results have important implications. Many studies use algorithms such as Lee-Ready to identify the initiating side of transactions in databases where the aggressor side of the trade is not readily available to researchers. Hence, order flow is already a noisy measure of traders aggressive trading. Our study shows that even in databases where the aggressor side of the transaction is accurately identified, order flow cannot fully reflect traders' intentions. It is also important to note that because our skewness measure is related to position build-up on one side of the market, there are more traders on the opposite side of this positioning. Hence, our results can also suggest that prices tend to move against the side that has the highest number of traders. In this context, traders herd on the liquidity providing side of the market.

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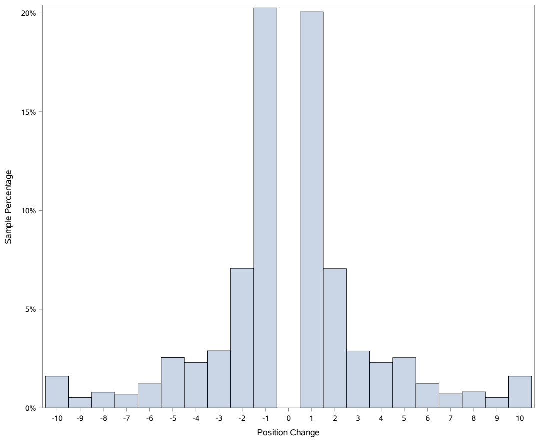
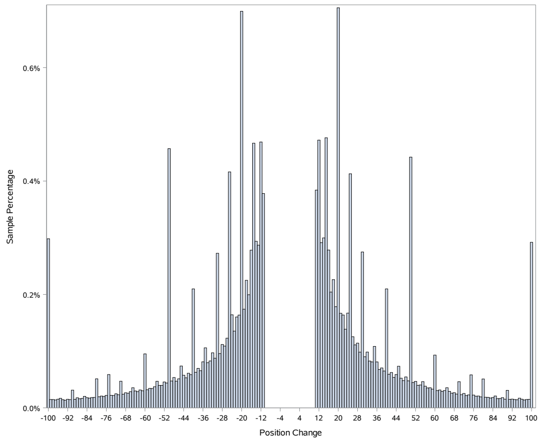
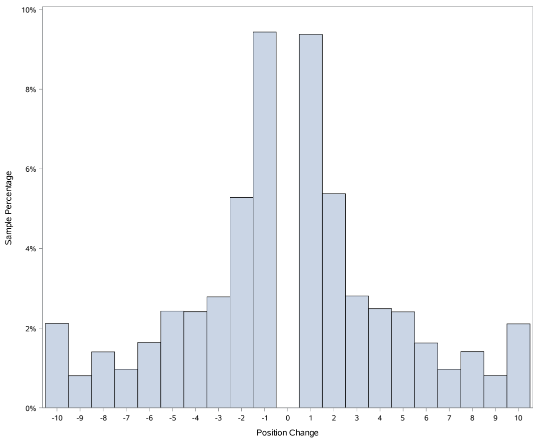
Figure 1: Distributions of One-Minute Net Position Changes



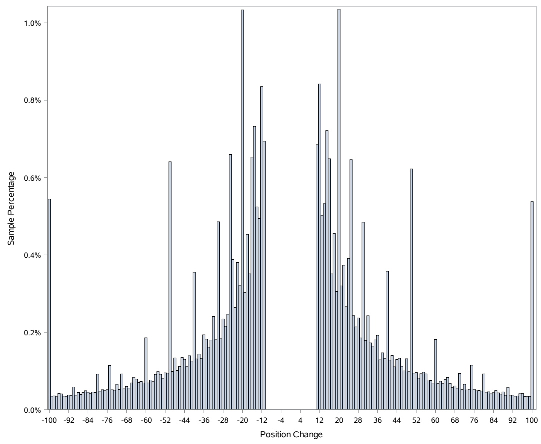
(a) ES: Net Position Changes 1 to 10



(b) ES: Net Position Changes 11 to 100



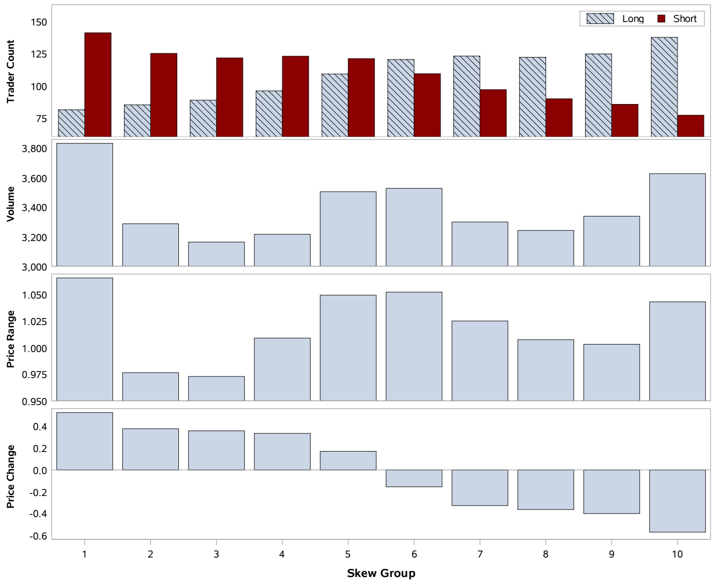
(c) 10Yr: Net Position Changes 1 to 10



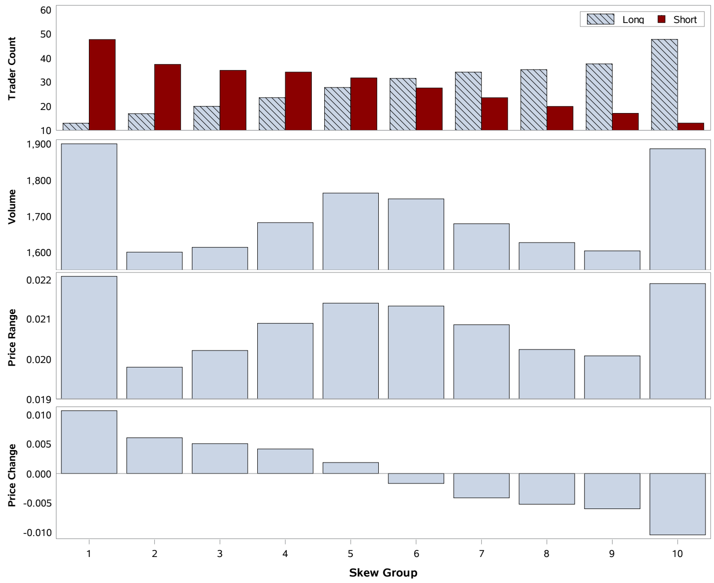
(d) 10Yr: Net Position Changes 11 to 100

The figure shows the distribution of one-minute position changes observed in the E-mini S&P 500 and 10-year Treasury futures markets for the entire sample. The charts on the left plot the position changes between -10 and 10 contracts. The charts on the right plot the position changes of greater than 10 contracts and fewer than -10 contracts.

Figure 2: E-Mini S&P 500 and 10-Year Treasury Futures Sample Stats by Skew Group



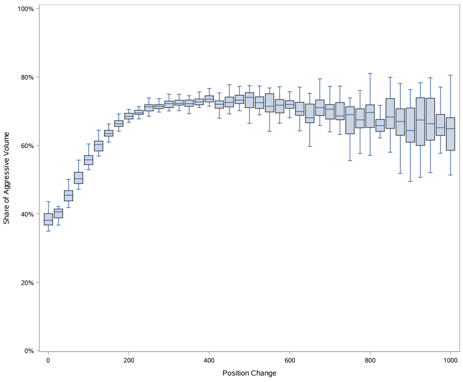
(a) ES



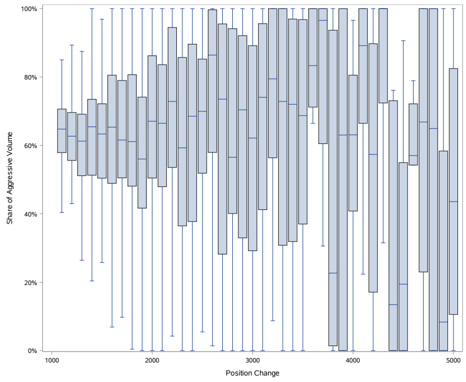
(b) 10Yr0

The figure shows sample statistics for one-minute intervals for E-mini S&P 500 and 10-year Treasury futures contracts. All statistics are presented across skewness groups, where the first group includes skewness values between 1 and .80; the second group includes skewness values between .80 and .60, and so on. The top panel displays statistics for S&P 500 E-mini futures contracts and the bottom panel displays statistics for the 10-year Treasury futures contracts. The first rows show average trader counts for traders who are net short (red) and net long (blue). The second rows show average volume, third rows display average price volatility (max price min price) and the fourth rows display average trade price change.

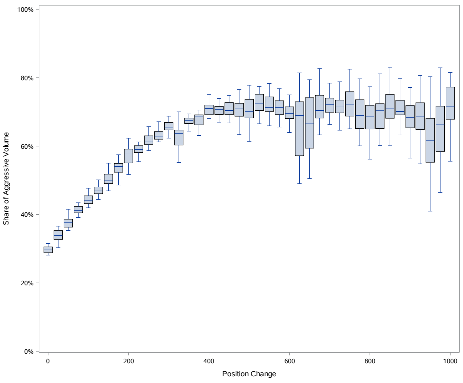
Figure 3: Aggressiveness Ratios for Position Changes for S&P 500 E-mini and 10-year Treasury Futures



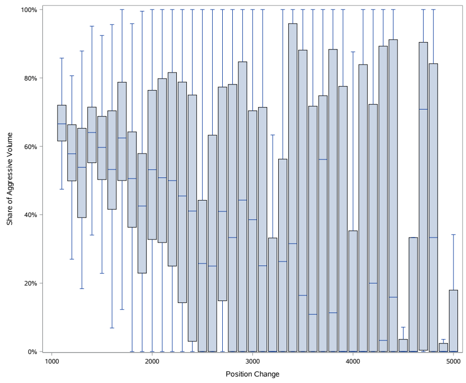
(a) ES: Set 1



(b) ES: Set 2



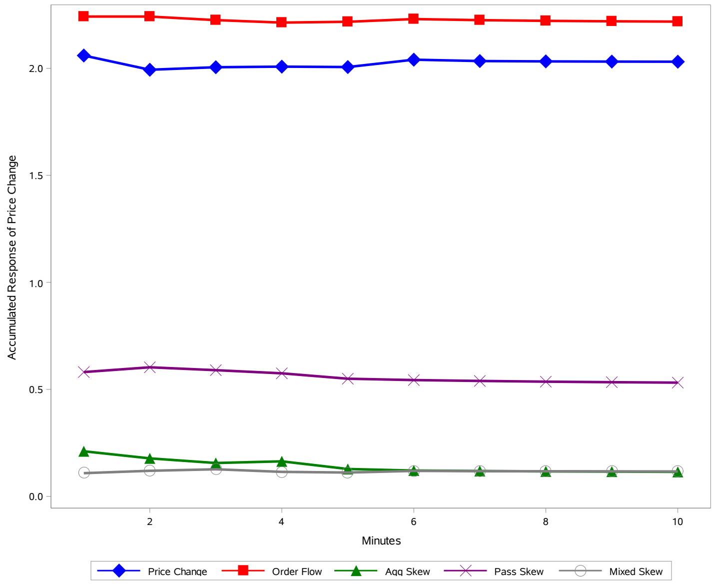
(c) 10Yr: Set 1



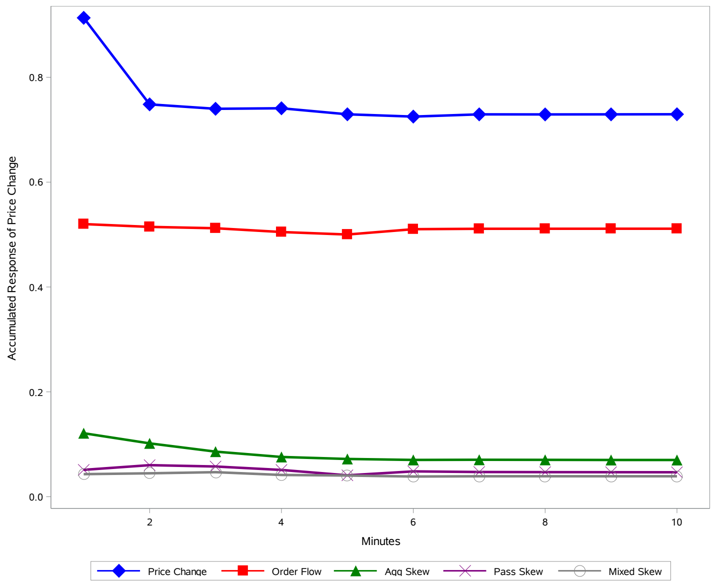
(d) 10Yr: Set 2

The figure plots the box plots of aggressiveness ratios for one-minute position changes averaged across days. The box plots show the maximum, 75th percentile, median, 25th percentile and minimum of this average aggressiveness ratio for various levels of position changes. The charts on the left plot absolute position changes of 1 through 1000, rounded by 25. The box plots on the right plot the absolute position changes of 1000 through 5000, rounded by 100.

Figure 4: Cumulative Impulse Response Functions



(a) ES



(b) 10Yr

The figure shows graphs that plot the change in prices (in number of ticks) for following 10 minutes in response to a one standard deviation shock to prices, order flow, aggressive skewness, passive skewness and mixed skewness variables.

Table I: E-Mini S&P 500 Futures

Panel A: Summary Statistics						
	Mean	Median	25th Pctl	75th Pctl	Std Dev	N
Price Change	0.01	0.00	-1.00	1.00	2.96	155,394
Order Flow	-0.01	-0.01	-0.34	0.32	0.79	155,394
Skewness	-0.04	-0.04	-2.69	2.61	4.43	155,394

Panel B: Correlations			
	Price Change	Order Flow	Skewness
Price Change	1.00	0.68	0.40
		<.0001	<.0001
Order Flow	0.68	1.00	0.41
	<.0001		<.0001
Skewness	0.40	0.41	1.00
	<.0001	<.0001	

The table shows the summary statistics for the S&P 500 E-mini futures market. Panel A reports the mean, median, quartiles, standard deviation of price changes, order flow and skewness measures calculated at one-minute intervals. Price change is in number of ticks (0.25 points), and order flow is the difference between aggressive buy and sell volume scaled in 1000 contracts. Skewness is the Fisher-Pearson population skewness coefficient of the trader position change distribution. Panel B reports the correlations coefficients among price change, order flow and skewness measures.

Table II: 10-Year Treasury Futures

Panel A: Summary Statistics	Mean	Median	25th Pctl	75th Pctl	Std Dev	N
Price Change	0.00	0.00	-1.00	1.00	1.09	142,844
Order Flow	0.00	0.00	-0.32	0.33	0.83	142,844
Skewness	0.00	0.01	-1.86	1.86	2.99	142,844

Panel B: Correlations	Price Change	Order Flow	Skewness
Price Change	1.00	0.51 <.0001	0.31 <.0001
Order Flow	0.51 <.0001	1.00	0.41 <.0001
Skewness	0.31 <.0001	0.41 <.0001	1.00

The table shows the summary statistics for the 10-year Treasury futures market. Panel A reports the mean, median, and standard deviation of price changes, order flow and skewness measures calculated at one-minute intervals. Price change is in number of ticks (1/64 points), and order flow is the difference between aggressive buy and sell volume in 1000 contracts. Skewness is the Fisher-Pearson population skewness coefficient of the trader position change distribution. Panel B reports the correlations coefficients among price change, order flow, and skewness measures.

Table III: Price Changes by Skewness and Order Flow Groups– S&P 500 E-mini futures

Order Flow	Skewness Groups								Test: +4 to −4	
Groups	−4	−3	−2	−1	+1	+2	+3	+4	Δ	t-stat
−4	-3.98	-3.58	-3.39	-3.12	-3.16	-2.66	-2.29	-1.68	2.29	24.08
−3	-1.82	-1.74	-1.68	-1.50	-1.30	-1.15	-0.90	-0.06	1.76	20.41
−2	-1.10	-0.98	-0.90	-0.81	-0.63	-0.50	-0.33	0.08	1.18	13.81
−1	-0.63	-0.48	-0.37	-0.26	-0.13	-0.03	0.12	0.43	1.06	13.87
+1	-0.40	-0.08	0.08	0.26	0.34	0.44	0.56	0.77	1.17	14.94
+2	-0.12	0.47	0.57	0.75	0.84	0.93	1.08	1.15	1.27	15.58
+3	0.27	1.05	1.18	1.38	1.71	1.78	1.78	1.81	1.54	17.10
+4	1.95	2.69	2.74	3.13	3.18	3.37	3.59	3.95	2.00	18.90

The table shows the price changes in number of ticks for different skewness and order flow groups for the S&P 500 E-mini futures. Each observation for the skewness and order flow variables are arranged into eight buckets ranging from the lowest, represented by −4, to the highest, represented by +4. The last two columns report the t-statistics for the tests of equality between price changes in the lowest and highest skewness groups.

Table IV: Price Changes by Skewness and Order Flow Groups– 10-Year Treasury Futures

Order Flow	Skewness Groups								Test: +4 to −4	
Groups	−4	−3	−2	−1	+1	+2	+3	+4	Δ	t-stat
−4	-1.05	-1.01	-0.96	-0.85	-0.82	-0.76	-0.66	-0.54	0.51	13.66
−3	-0.54	-0.54	-0.55	-0.46	-0.48	-0.42	-0.35	-0.24	0.30	6.70
−2	-0.29	-0.25	-0.22	-0.21	-0.18	-0.21	-0.17	0.00	0.28	6.65
−1	-0.09	-0.08	-0.06	-0.06	-0.05	-0.06	0.00	0.10	0.20	3.40
+1	0.01	0.08	0.05	0.06	0.04	0.05	0.09	0.14	0.13	2.24
+2	0.05	0.18	0.22	0.22	0.22	0.24	0.25	0.30	0.25	5.58
+3	0.24	0.35	0.46	0.45	0.52	0.53	0.56	0.54	0.30	6.71
+4	0.52	0.76	0.75	0.83	0.97	0.98	1.01	1.06	0.54	13.76

The table shows the price changes in number of ticks for different skewness and order flow groups for the 10-year Treasury futures. Each observation for the skewness and order flow variables are arranged into eight buckets ranging from the lowest, represented by −4, to the highest, represented by +4. The last two columns report the t-statistics for the tests of equality between price changes in the lowest and highest skewness groups.

Table V: Regression Results: Skewness Measure

	E-mini S&P 500 Futures		10-year Treasury Futures	
Intercept	0.02	0.02	0.00	0.00
	2.37	4.54	0.98	0.87
Skewness	0.27	0.10	0.11	0.60
	140.66	56.69	109.28	103.26
Order Flow		2.32		0.04
		168.23		40.33
N	155,394	155,394	142,841	142,841
Adj-R^2(%)	16.27	48.17	9.72	27.08

The table reports the regression results of price changes in number of ticks on order flow and skewness of the position change distribution in S&P 500 E-mini and 10-year Treasury futures markets. t-statistics are calculated from White standard errors.

$$\frac{\triangle P_t}{TickSize} = \alpha + \lambda OF_t + \beta Skew_t + \varepsilon_t$$

Table VI: Regression Results: Disaggregated Skewness

	E-mini S&P 500 Futures		10-year Treasury Futures	
Intercept	0.02	0.03	0.00	0.00
	2.98	5.14	1.75	1.06
Agg Skewness	0.23	0.05	0.08	0.03
	128.83	26.63	79.65	26.57
Pass Skewness	-0.05	0.10	-0.04	0.01
	-23.95	51.45	-32.08	10.23
Mixed Skewness	0.16	0.04	0.02	0.03
	30.85	11.50	8.22	11.28
Order Flow		2.70		0.60
		136.95		66.19
N	155,394	155,394	142,841	142,841
Adj-R^2(%)	25.69	49.02	18.26	26.74

The table reports the regression results of price changes in number of ticks on order flow and aggressive, passive and mixed skewness measure of the position change distribution in S&P 500 E-mini and 10-year Treasury futures markets. t-statistics are calculated from White standard errors.

$$\frac{\triangle P_t}{TickSize} = \alpha + \lambda OF_t + \beta_1 Skew_t^{Agg} + \beta_2 Skew_t^{Pass} + \beta_3 Skew_t^{Mixed} + \varepsilon_t$$

Table VII: High-Low Spread Estimator

	E-Mini S&P 500 Futures	10-Year Treasury Futures
P5	0.00	0.00
P25	0.00	0.00
Median	0.71	0.69
Mean	1.45	0.66
P75	2.37	1.20
P95	4.90	1.81
Std Dev	1.86	0.68
N	155,394	142,844

The table reports the summary statistics of the Corwin-Schultz (2012) spread estimator for the S&P 500 E-mini futures market and the 10-year Treasury futures market. The summary statistics include 5th, 25th, 50th (median), 75th , 95th percentiles as well as the mean and standard deviation of this spread estimator.

Table VIII: Regression Results: Bid-Ask Spread

	E-mini S&P 500 Futures		10-year Treasury Futures	
Intercept	0.02	0.03	0.00	0.00
	2.98	5.14	1.75	1.06
Lag H-L Spread	0.11	0.11	0.13	0.13
	22.72	22.48	38.65	38.65
abs(Order Flow)	-0.34	-0.40	-0.05	-0.06
	-41.34	-42.33	-17.07	-14.99
abs(Skewness)	0.01		0.00	
	5.56		-0.56	
abs(Agg Skewness)		0.005		0.000
		2.69		-0.31
abs(Pass Skewness)		0.03		0.003
		15.65		2.63
abs(Mixed Skewness)		0.02		-0.004
		5.82		-2.48
N	155,394	155,394	142,841	142,841
Adj-R^2(%)	2.23	2.50	1.81	1.82

The table reports the regression results of the Corwin-Schultz spread estimator on its lag, the absolute value of the order flow, and the absolute values of the skewness measure and its components for the S&P 500 E-mini futures and 10-year Treasury futures markets. t-statistics are calculated from White standard errors.