An Empirical Analysis of Predatory Trading

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Using account level trade data for Korean KOSPI 200 futures contracts, we provide compelling empirical evidence that large trades are systematically front-run by predatory traders. Our analysis indicates that predatory traders begin correctly building positions at least two hundred trades before the arrival of a large trade and begin to unwind their positions almost immediately after the arrival of the large trade consistent with the predictions of Brunnermeier & Pedersen (2005). We find that front-running increases transaction costs for large traders by exacerbating the price run-up just prior to the arrival of the large trade.

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1. Introduction

Large traders face a complex decision of when and how to expose their trading interests. If they underexpose their intent to trade they risk being unable to find a trading partner, however, if they over expose their trading intent they may face increased transaction costs by having their order front-run by predatory traders (Harris (1997), Brunnermeier and Pedersen (2005)). Front-running occurs when a predatory trader becomes informed of an impending trade and then transacts in front of that trade and in the same direction so as to profit from the price impact of the impending trade. Front running is a form of predatory trading, and increases transaction costs by exacerbating the price impact of the large trader's order.

Large traders have consistently complained about their orders being systematically front-run in the popular media (see for example Lewis (2014)). However, due to data limitations, convincing empirical evidence of such systematic front-running has been difficult to find. A few notable studies include Hirschey (2013) who, while silent about individual orders, provides evidence that high frequency traders tend to trade in advance of periods of large buying or selling pressure. It is unclear, however, in Hirschey's (2013) study whether the high frequency traders are acting in a predatory manner, because after successfully anticipating buying or selling pressure high frequency traders do not appear to unwind their positions to profit from the price impact as predicted by Brunnermeier and Pedersen (2005). Another related study by Clark-Joseph (2014) models how high frequency traders may be able to anticipate short term price changes by monitoring the market responses to small exploratory trades which they place. Tong (2015) and van Kervel and Menkveld (2016) both study the impact of high frequency trading on implementation shortfall. Other theoretical studies related to front-running include Yang and Zhu (2015), Li (2014), and Bernhardt and Taub (2008).

In this study we use account level transaction data for trading in Korean KOSPI 200 futures contracts for 66 consecutive trading days beginning March 26, 2009, and find compelling evidence that large orders are systematically front-run by predatory traders. We define large trades in the data as those trades which are among the top 1% of trades by size yielding 32,303 large trades. We then classify each of the 25,172 unique accounts in our data are defined as being either a large trader, a small trader, or a predatory trader (PT) based on trading behavior. When classifying PTs our goal is to isolate those accounts which aggressively trade short term price changes rather than long term fundamentals. To identify accounts that specialize in trading short term price changes we limit our definition of PTs to those accounts which (1) have an average holding time for a position of less than three minutes, and (2) have an average daily ratio of overnight inventory to daily trading volume that is less than 0.01%. To eliminate accounts that employ market making strategies, to be a PT an account must also meet the requirement that (3) the account trades with an active trade more often than with a passive trade. We define large traders as accounts that are not PTs, and that have at least one trade in the top 1% of trades by size. All other accounts are defined as small traders. This process yields 32 PTs, 737 large traders, and 24,403 small traders. The predatory traders are extremely active as a group. PTs, large traders, and small traders comprise 22.5%, 42.7% and 34.8% of total trading volume respectively. Our basic empirical strategy is to use an event study methodology to analyze the aggregate trading behavior of each of the three account types around the arrival of a large trade.

Our empirical results follow closely the theoretical predictions of Brunnermeier & Pedersen (2005). Our analysis indicated that PTs begin building up positions in the same direction as the incoming large trade up to 200 trades (approximately two minutes) before the arrival of the large trade. We find that the magnitude of the inventory accumulated by PTs is strongly associated with the magnitude of a price run-up just prior to the arrival of the large trade. After the arrival of the large trade, PTs immediately begin to unwind their accumulated positions. Our results indicate that 56.06% of large trades are successfully front-run by PTs. This proportion is statistically greater than 50%, and is fairly consistent over our entire sample.

We also perform an analysis of predatory trading that is unconditional of the arrival of a large trade. To accomplish this, we divide our sample into two minute segments and use the inventories of PTs to predict the net size and direction of the large trades which occur over the next two minutes. The unconditional results confirm the event study. We find that the size and direction of PTs inventory at the beginning of each two-minute period positively predicts the size and direction of large trades which arrive during the following two-minute interval.

As described by Brunnermeier and Pedersen (2005), the main cost of predatory trading to by large traders is the price run-up prior to the large trade caused by the predatory traders. Put very simply, by purchasing in the same direction as a large trade, predatory traders put price pressure on the security which moves the price in the same direction as the large trade before it occurs. The large trade then transacts a price somewhat less advantageous to the large trader than it would have otherwise. The arrival of the large trade places additional price pressure which moves the price further. After the arrival of the large trade and its subsequent price impact, the predatory traders exit their positions placing price pressure in the opposite direction, and the price stabilizes near where it would have been without the predatory traders. The price impact engendered by the large trade comprises the predatory trader's profit, and the difference between where the price would have been without the predatory traders when the large trade arrives, and where the price actually was, comprises the increased transaction cost born by the large trader.

We estimate both the cost born by the large trader, and the profits of the predatory traders. To estimate the cost born by large traders, we measure the price run-up prior to the large trade as the price change between the 200th trade before the large trade, and the last trade just prior to the large trade in basis points. We then measure how sensitive this price run-up is to the inventory positions accumulated by the PTs prior to the arrival of the large trade. Our results indicate that a one standard deviation increase in PT inventory correlates with an increase of 3.33 basis points in trade price prior to the arrival of the large trade.

To measure the profits to the PTs we simply compute the difference between the average cost that PTs incur to enter their positions and the average proceeds from exiting their positions. We estimate this separately from trades where PTs successfully and unsuccessfully front-run large orders. Our analysis indicates that PTs earn an average profit (loss) of 2.1 (1.6) basis points for each successfully (unsuccessfully) front-run large trade. This asymmetry between profit and loss for successful and unsuccessful attempts by PTs to front-run large orders suggests that PTs trade in a manner that mitigates losses to failed attempts, and maximizes gains. The main difference that we observe in PT trading behavior when they are successful and unsuccessful is that they exit their positions much more quickly when unsuccessful.

In our data, an average of 548 large orders arrive each day, and that PTs are able to reliablely front-run more than 50% of them. Consequently, an application of the Kelly criteria (Kelly, 1956) should allow PTs to earn consistent long-term profits. To test this idea, we calculate hourly and daily mark-to-market profits for the PTs in our sample and we find that hourly profits are positive 81% of the time and that the distribution of hourly mark-to-market profits exhibits positive skewness. Further, we find that of the 66 trading days in our sample, there is only one for which the daily mark-to-market profits of PTs are not positive.

We also explore the mechanisms which allow PTs to anticipate and front-run large trades. Large traders do not randomly execute large trades. It is well known that large orders are routinely shred into smaller child orders. These child orders placed in advance of the main order could, if properly identified, allow PTs to successfully predict the arrival of a large trade. We test two hypothesis related to these child orders which may give us insights into how PTs identify large trades. The first is that larger child orders will be easier to identify and thus will increase the likelihood that a large trade will be successfully front-run. The second hypothesis is related to speed. Since the KRX does not allow colocation and the Korean market is not fragmented, the main advantage to speed from a large trader's perspective is the ability to cancel orders quickly if market conditions turn against the large trade, and to be higher in the que and thus more likely to execute a trade without giving PTs the time to respond to a given order. To test the first hypothesis, we compute the average size of the child orders associated with a given large trade and then use regressions to determine if large trades associated with larger than average child orders are more likely to be front-run. To test the second hypothesis, we measure speed as the mean difference between order matching and submission times for all matched passive orders for a given large trader. We then use regressions to determine if large trades associated with slower than average execution time are more likely to be preyed upon. We find evidence consistent with both of the proposed hypothesis but our results indicate that child order size appears to be of greater economic magnitude than speed.

One alternative story may be that PTs are good at predicting short term price changes, potentially through analyzing the market responses to small exploratory trades as hypothesized by Clark-Joseph (2014). In this alternative story PTs are not deliberately front-running large trades, but only appear to because large trades are correlated with price changes. We use a VAR model to study the dynamic relation between trading by large traders, small traders, and PTs and price innovations. If PTs are targeting price changes, then we should observe that PT trading is positively correlated with price changes. Our results indicate that when controlling for the trading of large traders in our models, PTs actually trade in the opposite direction as contemporaneous price changes. However, when we exclude the contemporaneous trading of large traders in the specification PTs appear to trade in the same direction as contemporaneous price changes. These results are inconsistent with the idea that PTs are trading price changes, and suggest that PTs' trading is correlated with the trading of large traders, and that the trading of large traders is positively correlated with contemporaneous price changes. The portion of PT trading that is orthogonal to large trader trading actually trades in the opposite direction of current price changes.

The remainder of this paper is as follows. In section 2 we discuss our data and our methodology for dentifying PTs. In section 3 we provide our empirical analysis and in section 4 we conclude.

2. Data

We obtain data from the Korean Stock Exchange (hereafter KRX). Our data contains the complete record of account level trades and quotes for KOSPI 200 index futures time-stamped at the millisecond level. If multiple events occur in the same millisecond, the correct order of events is preserved in the data. Our sample begins on March 26, 2009 and continues for 66 consecutive trading days.

The KOSPI 200 Index consists of 200 large cap stocks listed on the KRX, and options and futures derived from the KOSPI 200 index are among the most liquid and highly traded derivatives in the world[1]. As a well-diversified basket of stocks, the KOSPI 200 index is less susceptible to stock specific idiosyncratic risk, providing a relatively clean environment with which to study trading activity. All KOSPI 200 contracts are traded electronically. The notional value of one KOSPI 200 index futures contract is the KOSPI 200 futures price times a multiplier of 500,000 Korean Won. This translates to the average notional value of one contract of approximately USD 68,000[2] during our sample. The tick size for KOSPI 200 index futures is 0.05 or 2.86 basis points (approximately USD 19.37).

Because back month contracts constitute a minority of trading and tend to be illiquid, we limit our analysis to front month contracts.[3] As June 11, 2009 is the only expiration day in our sample, prior to June 11 we study trading in contracts with a June 11 expiration date and after June 11 we study trading in contracts which expire on September 10, 2009. KOSPI 200 future contracts operate with a price limit of 10%. During our sample there were not any days with fluctuations severe enough to trigger the circuit breaker.

The granularity of our data allows us to sign order flow very accurately without relying on algorithms such as Lee and Ready (1991). We do this by simply ordering the events in a given trade. When two accounts complete a transaction, we observe both the time that the transaction was completed as well as the times that both traders submitted the orders which resulted in the transaction. If the buyer in a given trade submits his order after the seller does, then the buyer is determined to be the aggressive party and the trade

[1] See Ahn, Kang, and Ryu (2008) (2010)
[2] The average closing price for the KOSPI 200 index during our sample is 174.97 and the average USD/KRW exchange rate is 1,290.73.
[3] Including back month contracts does not qualitatively change our results.

is identified as a buyer-initiated trade. We can also observe latency between order submission and order fulfillment.

To facilitate our analysis, we define large trades as those trades which are in the top 1% of trades by size across our whole sample. We exclude large trades which occur in the first five minutes of trading, because predatory traders lack sufficient order flow to attempt to front-run at the very start of trading. We also exclude large trades which occur in the last five minutes of the trading day because predatory traders are less likely to front-run in this period because as short term traders, they are averse to holding inventory overnight, and thus they will be liquidating their inventories as the day closes. This process identifies 32,303 qualifying large trades. The smallest trade that qualifies as a large trade is for 50 contracts, or a notional value of approximately 3.4 million USD. As presented in Table 1, the mean size of a large trade is 78.76 contracts. Of the 32,303 large trades, 48.99% are buyer-initiated trades. Large trades occur an average of 548 times per day with an average time of 40 seconds between consecutive large trades.

<Insert Figure 1: Characteristics of Large Trades Here>

<Insert Table 1 Here: Characteristics of Large Trades Here >

In panel A of Figure 1, we present the distribution of large trades across the trading day in ten minute increments from 9:00 am until the close of the trading day at 3:15 pm. We observe, consistent with Jain & Joh (1988) and McInish & Wood (1990) that large trading volume has a U shape with more trading in the opening and closing of each day. We also plot in the ratio of large trades to small trades for each ten-minute increment, in panel A and we find that the ratio of large trades to small trades remains fairly constant throughout the day except for during the last 10 minutes of trading where the ratio nearly doubles, suggesting that large traders rush at the end of the day to complete their trades before the trading day concludes. In panel B of Figure 1, we plot the partial autocorrelation function for the sign of large trades, and we observe that the sign of large trades exhibits positive autocorrelation for up to six lags.

There are 25,172 unique accounts in our data. We classify each account based on trading behavior. Accounts are classified as either a predatory trader (PT), a large trader, or a small trader. When classifying PTs our goal is to isolate those accounts which aggressively trade short term price changes rather than long term fundamentals. To identify accounts that specialize in trading short term price changes we limit our definition of PTs to those accounts which (1) have an average holding time for a position of less than three minutes[4], and (2) have an average daily ratio of overnight inventory to daily trading volume that is less than 0.01%. To eliminate accounts that employ market making strategies which might meet these first two criteria, we also require a PT to meet the requirement that (3) the account trades with an active trade more often than with a passive trade. Large traders are defined as accounts that are not PTs, and that have at least one trade in the top 1% of trades by size. All other accounts are defined as small traders. This process yields 32 PTs, 737 large traders, and 24,403 small traders.

<Insert Table 2 here: Descriptive statistics for trader types>

In table 2 we present descriptive statistics for each of the three account types identified in our sample. In panel A we present statistics for the number of traders in each of our three trader classifications as well as additional statistics about whether these accounts are foreign (non-Korean) or domestic (Korean), or retail or institutional accounts. Most of the PTs identified in the sample are Korean institutional investors, although there are five foreign accounts which meet our criteria for predatory traders. In panel B of Table 2 we present volume statistics by trader group. PTs in our data account for 22.5% of all trading volume. Large traders account for 42.7% of trading volume, and small traders comprise the remaining 34.8% of trading volume. Consistent with our definition, PTs are the initiating counterparty party in 30.5% of all trades and are the passive party in 14.5% of all trades. Large trades comprise 14% of trading volume while small trades comprise the remaining 86% of trading volume.

[4] We define one position as a sequence of trades which maintains the same sign of inventory. For example, a long positon starts from a zero-inventory position and remains as long as inventories are positive.

In panel C of Table 2 we present descriptive statistics for the trading behavior of each of the three classes of investor. The first statistic that we calculate is the number of times an account's position switches from long to short or from short to long in a day. We find that the inventory for the median PT switches direction 27 times more than the median small trader and 40 times more frequently than the median large trader. Consistent with our definition, PTs hold essentially zero overnight inventory whereas large and small traders carry a significant portion of their daily trading volume overnight.

3. Empirical Analysis

3.1 Predatory Trading

As Brunnermeier & Pedersen (2005) point out, markets must exhibit some degree of illiquidity in order for front-running to be profitable. If this were not the case then new trades, regardless of the size, would not have any price impact and front-running them would not be profitable. To understand the price dynamics around a large trade we use an event study. Price is denoted as $p(i,j)$ where i indexes the large trade and j indexes the trading sequence around the i^{th} large trade where $j = 0$ indicates the price at the large trade. Since we are concerned with the effect a large trade has on price changes, we define the relative price as presented in equation 1.

$$p'(i,j) = \ln\left(\frac{p(i,j)}{p(i,0)}\right) * 10\text{^}4 \tag{1}$$

For our event study we compute the average relative price across all large trades for each relative trading position j beginning at $j = -200$ and ending at $j = 200$ as presented in equation 2.

$$\overline{p'(j)} = \frac{1}{N}\sum_{i=1}^{N} p'(i,j) \tag{2}$$

In equation 2, N is the number of large trades in the sample. Because large buyer-initiated trades are likely to be associated with price increases and seller-initiated trades are likely to be associated with price declines we calculate $\overline{p'(j)}$ separately for buyer and seller-initiated large trades. This process yields two series displaying the average price dynamics around large trades beginning 200 trades before the large trade and ending 200 trades after the arrival of the large trade. Our results are presented in Figure 2. We observe that for both large buys and large sells, the price tends to drift in the direction of the large trade up to 200 trades prior to the execution of the large trade. Then at the moment of the large trade, the price gaps in the direction of the large trade, and then remains fairly stable for the 200 trades following. When converted to basis points, the average price gap up for large buys is approximately .7 basis points and the price gap down for large sell trades is approximately 1.5 basis points. The analysis presented in Figure 2 demonstrates that large trades do generate price impact and thus PTs can potentially profit if they can successfully build up positions before the large trade and then unwind them afterward.

<Insert Figure 2 Here: Price Dynamics Around Large Trade>

To study the behavior of the different classes of traders around large trades, we once again use an event study. We analyze large buys and large sells separately and we divide our sample into four groups of traders including: large traders engaging in the given large trade, large traders not engaging in the large trade, PTs, and small traders. Since we are concerned with changes in inventory around a large trade we normalize the inventory of all groups to be equal to zero 200 trades before the arrival of the large. For each trading position $j \epsilon[-200,200]$ [5] we compute the average holding for each investor class across all large trades in the given sample. This process yields four sequences representing the average inventory accumulations for each of the four groups around the arrival of a large trade. For illustration purposes we perform this analysis for large buys and sells, and for when PTs are on the correct and incorrect side of a large order. Analyzing trading behavior for large trades when PTs are on the correct and incorrect side of the market when the large trade arrives allows us to study how PTs trade when they correctly front-run a large order so as to maximize profit, and how they trade after incorrectly front-running a large trade so as to minimize losses. We find that 26.83% (22.16%) of large trades are large buys where PTs successfully (unsuccessfully)

[5] In our data approximately 100 trades arrive every minute and thus 200 trades equals approximately two minutes of real time elapsing.

accumulate positions in the same direction as the large trade before its arrival, and that 29.23% (21.78%) of large trades are large sells where PTs successfully (unsuccessfully) accumulate positions in the same direction as the large trade before its arrival. These numbers indicate that PTs are successful in front-running 54.77% of large buy orders and 57.39% of large sell orders for a total of 56.06% of all large trades.

<Insert Figure 3 Here: Trading Dynamics Around Large Trades>

In panels A and B of figure 3 we present the results of our event study for large buys when PTs accumulate positions in the same and opposite direction as the large trader respectively. In panels C and D of figure 3 we present the results for large sells when PTs accumulate positions in the same and opposite direction as the large trader respectively. We find across all four panels that PTs begin to aggressively accumulate positions up to 200 trades prior to the arrival of the large trade, and begin to unwind their positions almost immediately after the arrival of the large trade. This behavior is consistent with the predictions of Brunnermeier & Pedersen (2005). The magnitude of the size of the positions accumulated by PTs is significant and is equal to approximately 30% of the size of the average large order. The key difference in PT behavior when they have accumulated inventories on the same side as the large trade compered to when their positions are on the opposite side of the large trade is that after an unsuccessful attempt to front-run a large order the PT exits their position much more quickly than they do when on the same side as a large order.

We also observe in figure 3 across all panels that large traders executing the large trade begin to accumulate inventory well in advance of the large trade, although not as aggressively as do the PTs, suggesting that the large traders transacting the large trade engage in order smoothing. Small traders and large traders not executing the large trade serve as counterparties trading against the PTs and the large traders who are seeking to execute a large trade. In panels A and C we observe that when PTs successfully front-run large orders, after the arrival of the large trade, small investors switch from trading in the opposite direction of the large trade, to the same direction immediately after. This behavior is convenient for the

PTs because it provides a counterparty willing to accept the positions of the PTs allowing the PTs to unwind their positions with reduced price impact.

For PTs to profit from front-running a trade there must be price impact. In figure 4 we use the same methodology as was employed in figure 2 and we plot the average relative price around large buy and sell trades for trades where the PTs successfully front-run the large trade, and where they unsuccessfully front-run. In panels A and B we present the price dynamics for large buy orders when PTs are successful and unsuccessful at front-running the large trade respectively. In panels C and D we present the price dynamics for large sell orders when PTs are successful and unsuccessful at front-running the large trade respectively. In panel A and C where we plot the price dynamics around successful attempts by PTs to front-run we observe price behavior consistent with Brunnermeier and Pedersen (2005). Prior to the large trade there is a run-up in price, followed by a jump in price corresponding to the arrival of the large trade, and after the arrival of the large trade, the price reverts somewhat as the PTs exit their positions. The price dynamics are somewhat different when PTs are unsuccessful in their attempt to front-run the large order. We observe a milder run-up in price, but the run-up is in the opposite direction as the incoming large order. There are two potential reasons why this price run-up is in the opposite direction as the large order. The first is that the price run-up is exogenous to the decisions of the PTs, and is a part of the explanation of why the PTs took positions on the wrong side of the large trade. The second reason is that by trading aggressively in the opposite direction of the incoming large trade the PTs are causing the price run-up to be in the opposite direction. After the arrival of the large trade, we do not observe a price reversal as we do when PTs are successful. When PTs are unsuccessful the price after the large appears to continue to drift in the same direction as the large trade as PTs quickly unwind their incorrect positions, which implies that they trade in the same direction as the large trade.

<Insert Figure 4 Here: Price Dynamics Around Large Trades for Success and Unsuccess>

The analysis heretofore has been mostly informal. To formally test the null hypothesis that the probability of PTs being on the right side of large trades is less than or equal to 50%, we use a simple regression. For this analysis we define $Sign_i$ as the sign of the i^{th} large trade and is equal to -1 for large sells and 1 for large buys. We define $SignPT_{k,i}$ as the sign of the k^{th} PT accounts inventory at the time of the i^{th}large trade. $SignPT_{k,i}$ is either 1 or -1 indicating whether or not the k^{th} PT was long or short at the time of the i^{th}large trade. Because large orders are autocorrelated, we control for the sign of the prior 15 large orders in our regressions. We also include fixed effects for each of the 32 PTs in our sample. Our base model for our hypothesis test is presented formally in equation 3.

$$Sign_i = \beta_0 SignPT_{k,i} + \sum_{j=1}^{15} \gamma_j Sign_{i-j} + \alpha_k + \varepsilon_i \qquad (3)$$

From equation 3 testing the hypothesis that $\beta_0 \leq 0$ is equivalent to testing the null hypothesis that PTs predict the sign of large orders with a probability greater than random chance. In panel A of Table 3 we present the results from our regressions. We estimate three variations of equation 3. The first is a simple OLS model where we do not include the values for lagged $Sign_i$ or fixed effects for the 32 PTs in our data. In the second variation we include PT fixed effects but we do not include the values for lagged $Sign_i$, and the last model is the whole model presented in equation 3. We find that across all of these specifications the coefficient for β_0 is significantly greater than zero, leading us to reject the null hypothesis that PTs ability to anticipate the sign of large orders is due to random chance.

In panel B of Table 3 we estimate similar regressions to those in panel A except that we multiply $Sign_i$ by the size in contracts of the i^{th} large trade and $SignPT_{k,i}$ by the size of PT k's position at the time that the i^{th} large order arrives. These specifications yield the same result. We reject the null hypothesis that PTs ability to anticipate the sign of large orders is due to random chance.

<Insert Table 3 Here: Regressions About Random Chance>

To determine if our results are driven by a certain time period within our sample, or are general throughout the sample, we divide our 66-day sample period into 33 two day sub-periods and estimate equation 3 for each of the two-day sub periods. In Figure 5 we plot the results for β_0 for each of the 33 sub-periods. From these regressions we find that in none of the two-day sub-periods does the estimated value for β_0 become statistically negative, and in 28 of the 33 two-day sub-periods β_0 is greater than zero. Further the 5 periods where the observed β_0 is less than zero do not appear to be clustered in any given time period. The first event occurred in the 1st two-day time period and the last occurred at the 30th two-day time period. These findings suggest that the PTs front-running abilities are fairly consistent throughout the sample period.

<Insert Figure 5 Here: Stable Beta>

Our analysis up to this point is subject to the criticism that it is conditional on a large trade arriving and that the front-running behavior we document may be related to other trading strategies which occur independent of large trades. To ameliorate these concerns, we perform an unconditional analysis of predatory trading by using PT inventories to predict the direction of large trades. For this analysis we divide our sample into 2-minute segments and for each 2-minute segment we compute $y_{(t,t+1]}$ as the number of buyer-initiated large trades minus the number of seller-initiated large trades which arrive during time segment t. We calculate x_t as the sign of the aggregate inventory positions of PTs at time t, and $x_{(t-i,t-i+1]}$ is the sign of PTs net trades between time $t-i$ and $t-i+1$. We then use the predictive regression model presented in equation 4 to determine if PT inventories predict the arrival of large trades.

$$y_{(t,t+1]} = \beta_0 + \beta_1 x_t + \sum_{i=1}^{5} \beta_{i+1} x_{(t-i,t-i+1]} + \varepsilon_{(t,t+1]} \tag{4}$$

In this regression the key coefficient is β_1 which tests whether the inventory position of PTs at the beginning of time period t predicts the aggregate direction of large trades which will arrive between time period t and $t+1$. Since this is a time series regression we control for autocorrelation in the residuals by employing the Newey and West (1994) methodology with 30 lags. Our results for this specification are presented in Panel A of Table 4. We find in these regressions that β_1 is positive and statistically significant implying that PT inventories at time t positively predict the sign of aggregate large trading over the following 120 seconds. In Panel B of Table 4 we use the actual size, in number of contracts, of the aggregate large trades which arrive during a given 2-minute interval along with the actual size of PT positions to perform the same analysis. Here we find the same results. The size and direction of PT positions at time t positively predicts the size and direction of aggregate large trading during the following 2-minutes. As a robustness we estimate in Table 5 equation 4 but varying the window length from 5 seconds to 240 seconds. In addition to providing a robustness check, varying the time window allows us to study the time horizon that PT inventories predict future large trades. If we observe that the coefficient for x_t is monotonically increasing in the window length up until a point at which the coefficient remains relatively stable, then this would indicate that PT positions predict large order flow up to a given time and not after. We find that the coefficients from 5 seconds to 240 seconds are monotonically increasing with time. This result suggests that PT inventories predict the direction of upcoming large trades for up to 240 seconds.

<Insert Table 4 Here: Unconditional Regression Analysis>

<Insert Table 5 Here: Unconditional Regression Analysis>

The results from this section demonstrate that at least some PTs can and do successfully front-run large orders with greater than random probability. One significant element of these findings is that the capacity to front-run by PTs does not appear to be a function of latency as suggested in the popular media by Lewis (2014). The Korean exchange is not fragmented, and at the time of our data it did not allow colocation, further PTs begin correctly accumulating positions minutes before the arrival of the large trade. These findings are consistent with PTs being able to front-run by analyzing order flow, and using it to predict large orders, rather than PTs observing a trade on one market and racing to beat the arrival of the trade on a separate venue.

3.2 Determinates of Predatory Trading

In this section we turn our attention to trying to understand the mechanism which allow PTs to front-run. There are two competing hypotheses about the mechanisms that front-running PTs use to anticipate large trades. The first is the size of the child order. Harris (1997) argues that investors face a tradeoff between trading and exposing intent. If too much intent is exposed then the way is opened for predatory traders to exploit that intent, however if not enough intent is exposed then traders will fail to execute a trade. Likewise, market makers in Kyle (1985) respond to aggregate order flow by making the market thin when they expect that informed traders will demand large amounts of liquidity. This hypothesis suggests that the more that large traders expose intent through their child orders are more likely they are to be preyed upon by PTs. The second idea is that PTs use their speed to front-run traders. Since the Korean Market is not fragmented speed does not refer to the ability to observe a trade on one market, and then race to another market in advance of the incoming trade as might be argued in a fragmented market. Speed in the context of our analysis refers to the ability to quickly react to changes in the market environment and is measured by the average time between submission and fulfilment of a given order for a given account. Clark-Josep (2014) and Hirschey (2013) both argue that PTs can front-run order flow due to their speed advantage, and Li (2014) generates a theoretical model in which PTs anticipate order flow due to their speed. This hypothesis suggests that large traders who are slower at transacting are more likely to be front-run because it takes more time for them to respond to changes in the trading environment.

To test these hypotheses, we compute simple metrics for large trader intent exposure, and large trader speed. We use average child order size as a measure of intent exposure. The assumption implicit in this metric is that large trades associated with larger than average child orders will be easier for a PT to identify. For each large trade i executed by large trader l we calculate the average order size transacted by large trader l beginning three large trades prior to the arrival of the given large trade. Since large trades arrive on average every 40 seconds, this amounts to the average trade size for large trader l approximately 120 seconds before large trader l executes large trade i. This process produces an average child order size for each large trade in our sample. We then sort all large trades by their corresponding average child order size and identify those large trades with child order sizes in the largest 50% as having large child orders.

To measure large trader speed we calculate for each of the 737 large traders in our sample the average difference in time between order submission and order fulfillment for all passive orders that a large trader executes in our sample. We then sort large traders by average execution speed and those large traders in the slowest 50% of large traders are identified as being slow traders. We measure latency using passive orders as opposed to aggressive orders because If an order is an aggressive order, then the time between order arrival and execution time is determined by the exchange and not the trader. Passive trades are filled in the order that they arrive in the order book, and we expect that traders with lower latency will consistently be higher in the order book because of their quicker response time and will thus have their passive orders fulfilled more quickly.

We use regression analysis to determine if large orders associated with large child orders, or slow traders are more likely to be front-run. We test the two hypothesis that child order size and speed play a role in front-running dynamics separately and jointly by including child order size and large trader speed into the initial regression presented in equation 3 used to test the hypothesis that PTs can front-run large trades with greater than random change that as shown in equation 5.

$$Sign_i = \beta_0 + \beta_1 SignPT_{k,i} + \beta_2 SignPT_{k,i} * Child_i + \beta_3 SignPT_{k,i} * Speed_i + \beta_4 SignPT_{k,i} * Child_i * Speed_i + \sum_{j=1}^{15} \gamma_j Sign_{i-j} + \alpha_k + \varepsilon_i \quad (5)$$

In equation 5 $Sign_i$ is the sign of the i^{th} large trade, and $SignPT_{k,i}$ is the sign of the k^{th} PT's inventory at the moment of the i^{th} large trade. The variable $Child_i$ is an indicator variable identifying whether large trade i is associated with child orders that are larger than average. The variable $Speed_i$ is an indicator variable identifying whether or not large trade i is executed by a large trader that is slower than average. In our prior analysis the coefficient β_1 was used to test the hypothesis that PTs could front-run large orders with greater than random chance. In this specification, the coefficients β_2 and β_3 test the hypothesis that child order size and speed respectively affect the likelihood that a given large trade will be correctly anticipated by PTs. A positive coefficient for β_2 would indicate that large trades associated with larger than average child orders are more likely to be front-run by PTs. Likewise, a positive coefficient for β_3 would indicate that slower large traders are more likely to have their large orders front-run by PTs. The coefficient β_4 tests the joint hypothesis that the size of child orders and the speed of the large trader interact to affect the probability that a large trade will be successfully front-run by PTs. A positive coefficient for β_4 would indicate that child order size and speed interact to make large trades executed by slow large traders and associated with large child orders additionally likely to be front-run by PTs. We present our results for these regressions in Table 6.

<Insert Table 6 Here: Determinates of Front-running>

Our analysis provides evidence that both child order size and speed play a role in allowing PTs to front-run large orders, but that child order size appears to play a larger role in explaining the front-running ability of PTs. In our first specification we exclude variables relating to speed and test independently the size hypothesis. We find that the coefficient for the interaction between child size and the sign of PT positions is positive and is equal to 0.11 which means that large trades associated with larger than average child orders are 5.5% more likely to be front-run. It is also interesting to note that after controlling for child order size, the coefficient for the sign of PT inventory at the time of large trade is negative. This result suggests that child order size is essential in allowing PTs to front-run, and that after controlling for child order size, PTs are more likely to be on the wrong side of a large trade.

Our results for the effect of speed support the idea that PTs are more likely to front-run slower large traders, but the effect is not nearly as large. We find that PTs are 1.3% more likely to front-run large trades executed by slow large traders. We do not however find that the coefficient for the sign of PT inventory at the time of the large trade is negative, suggesting that the speed of the large trader has a lesser impact than does the size of the child order.

Lastly in our third specification we estimate the full model presented in equation 5. Our results from this specification confirm what our prior analysis indicates, which is that child order size appears to play a larger role in determining PTs ability to successfully front-run a large trade. The coefficient for the interaction of speed and child order size is positive and significant, indicating that large trades associated with large child orders and slow traders are additionally likely to be front-run by PTs. These findings provide evidence that both child order size and speed play a role in PTs' ability to front-run large orders, but that child order size appears to play a larger role in the Korean market.

One alternative story may be that PTs are good at predicting short term price changes, potentially through analyzing the market responses to small exploratory trades as hypothesized by Clark-Joseph (2014). In this alternative story PTs are not deliberately front running large trades, but only appear to because large trades are correlated with price changes. To study this distinction, we use a vector autoregression (VAR) to model the relation between trading by our three groups of traders and price changes in a dynamic setting. This allows us in a dynamic framework to determine if PT trading is correlated with price changes, or with the trading of large traders.

We use the arrival of each large trade as our separation point, and we define price changes as $\Delta p_{t,t+1} = \ln\left(\frac{p_{t+1}}{p_t}\right) * 10^4$ where p_t is the price at the t^{th} large trade. We also define $Large_{t,t+1}$, $PT_{t,t+1}$, and $Small_{t,t+1}$ as the net signed active trades of large traders, PTs, and small traders respectively between the t^{th} and the $(t+1)^{th}$ large trade. We use active trades because these are likely to contain information, and thus are more likely to be correlated with price innovations. For notational convenience we define the matrix X_t as in Equation 6.

$$X_t = \begin{bmatrix} \Delta p_{t,t+1} \\ Large_{t,t+1} \\ PT_{t,t+1} \\ Small_{t,t+1} \end{bmatrix} \tag{6}$$

We will also define the matrix Λ_t as in equation 7.

$$\Lambda_t = \begin{bmatrix} \lambda_{12} Large_{t,t+1} + \lambda_{13} PT_{t,t+1} + \lambda_{14} Small_{t,t+1} \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{7}$$

The matrix of coefficients Γ_i is defined as follows in equation 8.

$$\Gamma_i = \begin{bmatrix} \gamma_{11,i} & \gamma_{12,i} & \gamma_{13,i} & \gamma_{14,i} \\ \gamma_{21,i} & \gamma_{22,i} & \gamma_{23,i} & \gamma_{24,i} \\ \gamma_{31,i} & \gamma_{32,i} & \gamma_{33,i} & \gamma_{34,i} \\ \gamma_{41,i} & \gamma_{42,i} & \gamma_{43,i} & \gamma_{44,i} \end{bmatrix} \tag{8}$$

We then estimate the VAR model represented in equation 9.

$$X_t = \gamma_0 + \Lambda_t + \sum_{i=1}^{5} \Gamma'_i X_{t-i} \tag{9}$$

<Insert Table 7 here: VAR analysis>

In panel A of table 7 we present the results for price innovations for various specifications of equation 9. If PTs are predicting price changes then we will expect that the coefficient estimating the effect of contemporaneous trading on price innovations to be positive. In column one, where we present the results for the entire model, we find that the effect of PT trading on contemporaneous price changes is actually negative, and that prior PT trading has very little effect on contemporaneous price innovations. In specifications two and three we remove from the model the contemporaneous trading of large traders and the effect reverses. In these specification both contemporaneous and past PT trading positively predicts current price innovations. In specification four we exclude only the contemporaneous trading of small traders, but include the contemporaneous trading of large traders and we observe once again that PT trading is negatively associated with price innovations. These results are inconsistent with the idea that PTs are trading price changes. They suggest that PTs' trading is correlated with the trading of large traders, and that the trading of large traders is positively correlated with contemporaneous price changes. After controlling for large trader trading activity, PTs actually tend to trade in the wrong direction of price innovations. These results are supportive of the notion that PTs are targeting the large trades themselves rather than price movements.

3.3 Costs and Profits of Predatory Trading

In this section we analyze the costs to large traders of front-running, as well as the profits accruing to PTs due to their front-running behavior. As discussed by Brunnermeier Pedersen (2005), the costs born by large traders of front-running are due mainly to the increased price run-up prior to the arrival of the large trade caused by the PTs' trades. To measure this cost born by large traders, we estimate the sensitivity of price to PT trading in the run-up to the large trade. For each large trade we compute the net position of aggregate PT inventory accumulated between 200 trades prior to the large trade, and the trade immediately prior to the large trade. We then compute, in basis points, the change in price of the large trade from 200 trades prior to the large trade to the price immediately prior to the large trade. We divide PT inventory by its standard deviation for ease in interpretation, and we use a univariate regression to determine the sensitivity of price run-up prior to the large trade to PT inventory accumulation. Our analysis indicates that a one standard deviation increase in PT inventory accumulation corresponds to a statistically significant price run-up of 3.4 basis points. This represents a material cost born by large traders. Given that the average large trade has a value of approximately 5.3 million USD, an increase of 3.4 basis points represents a cost of approximately 1,800 USD born by large traders.

The profit accruing to PTs is due to the price impact of the large trader. We can estimate PT profits from front-running by using our results from section 3.1. In Figure 3 we observe the front-running dynamics of PTs both before and after a large trade both for when PTs are successful and when the PT is unsuccessful at front-running the large trade. By combining our analysis of trading behavior from Figure 3 with that of average price movements in Figure 4 we can estimate the average relative price paid for a PTs position and what PTs earn from unwinding their positions. Our analysis indicates that PTs begin building up positions at least 200 trades in advance of the large order. By taking the average relative price at order position j from Figure 4, and multiplying by the average number of shares purchased at order position j

from Figure 3, we compute the weighted average relative price that PTs pay to build a position prior to a large trade, and then likewise the average price that PTs receive to unwind their positions after the large trade arrives. Since we compute PT trading, and price dynamics for both when PTs are correct and incorrect for buys and sells separately we can compute the average profit and loss due to correctly or incorrectly front-running a given large buy or sell order. Our event study also provides us information for how many contracts on average the PT buys and sells to front-run a given large order. Using this information, we compute an average dollar amount to PT profits and losses per large trade.

We estimate that the profit for successfully front-running a large buy order is about 2.05 bps and 2.08 bps for a large sell order. Losses to incorrectly front-running a large buy order amount to approximately 1.69 bps and the losses to incorrectly front-running a large sell order amount to approximately 1.44 bps. In our sample, PTs successfully front-run 54.77% of large buy orders and 57.37% of large sell orders. Using the average size of PT positions in US dollars around large trades we find that PTs earn a profit of $493 for successfully front-running a large buy or sell order, and PTs accrue losses of $361 for incorrectly front-running a large buy order. Likewise, PTs earn profits of $492 for each successfully front-run large sell order and they accrue losses of $367 for incorrectly front-running a large sell order. Since an average of 548 large trades arrive each day, and in our sample 49% of large trades are buys and 51% are sells, it is straightforward to estimate the average daily mark-to-market profits generated by PTs from front-running orders in the top 1% of trades. Our estimate is that the PTs in our sample earn $63,447 of mark-to-market profit per day, or approximately $16 million in mark-to-market profit per year from front-running large KOSPI 200 futures contract trades. This number undoubtedly understates the true magnitude of the profits that the PTs in our sample earn because there is no reason why these firms cannot front-run large orders in other securities such as equities, or other large orders that we do not consider because, while still large, they do not fall into the category of top 1% by size and are thus outside the purview of this study.

While PTs appear to earn profits from front-running, it may be the case that PTs are engaged in other behavior which is not profitable, and thus on aggregate the PTs do not earn significant profits. We investigate the consistency of PT profits by dividing our sample into one hour segments and calculating the aggregate mark-to-market profits for PTs for each hour separately. In computing this we aggregate all PT positions together into one series. At the beginning of each one-hour segment we impose that PT inventories are equal to zero, we then track the profits and losses on all trades throughout the one-hour time period. At the end of the one-hour time segment we liquidate any remaining inventory at the current market price to compute the final mark-to-market profit or loss for the given one-hour segment. This process yields 66 days multiplied by 6 hour segments =396 observations. We normalize mark-to-market profits by dividing by their standard deviation and present a histogram of normalized hourly mark-to-market PT profits in figure 6. We observe in figure 6 that hourly mark-to-market profits are positive 80.85% of the time, and that the distribution of hourly mark-to-market profits exhibits positive skewness.

<Insert Figure 6 Here: Histogram of Mark-to-market Profits>

4 Conclusion

In this paper we study predatory trading in KOSPI 200 futures contracts. We find that predatory traders are able to successfully front-run 56.06% of large trades. Predatory traders begin accumulating positions at least 200 trades prior to the arrival of the large trade. After the arrival of the large trade, predatory traders quickly begin to unwind their positions consistent with the predictions of Brunnermeier & Pedersen (2005). We also find that successful front-running of large orders leads prices to follow the pattern predicted by Brunnermeier & Pedersen (2005), namely that there is a price run-up prior to the arrival of the large trade as PTs build their positions, and then a price reversal after the large trade as PTs unwind their positions. We investigate two competing hypothesis related to front-running. Specifically, we investigate the hypothesis that large trades associated with larger than average child orders will be more likely to be front-run because large child orders expose more intent to trade suggested by Harris (1997). We also test the prediction that slower traders will be more likely to be front-run because of an inability to react quickly to changes in the market environment. We find evidence for both hypothesis, but our results support the idea that child order size is of greater magnitude.

We find that the ability for PTs in our sample to front-run large trades if fairly constant throughout our sample, and that PTs hourly mark-to-market profits are positive 80% of the time. As suggested by Brunnermeier & Pedersen (2005) the main cost born by large traders of having their trades front-run is the additional price run-up prior caused by the inventory accumulation of the large traders. This price run-up causes large traders to transact their large trade at a price that is less advantageous than they would otherwise. We find that a one standard deviation increase in PT inventories accumulated just prior to the large trade corresponds to an increased price run-up of 3.4 basis points, which represents the cost born by large traders of being front-run. We estimate that the profit for successfully front-running a large buy order is about 2.05 bps and 2.08 bps for a large sell order. Losses to incorrectly front-running a large buy order amount to approximately 1.69 bps and the losses to incorrectly front-running a large sell order amount to approximately 1.44 bps.

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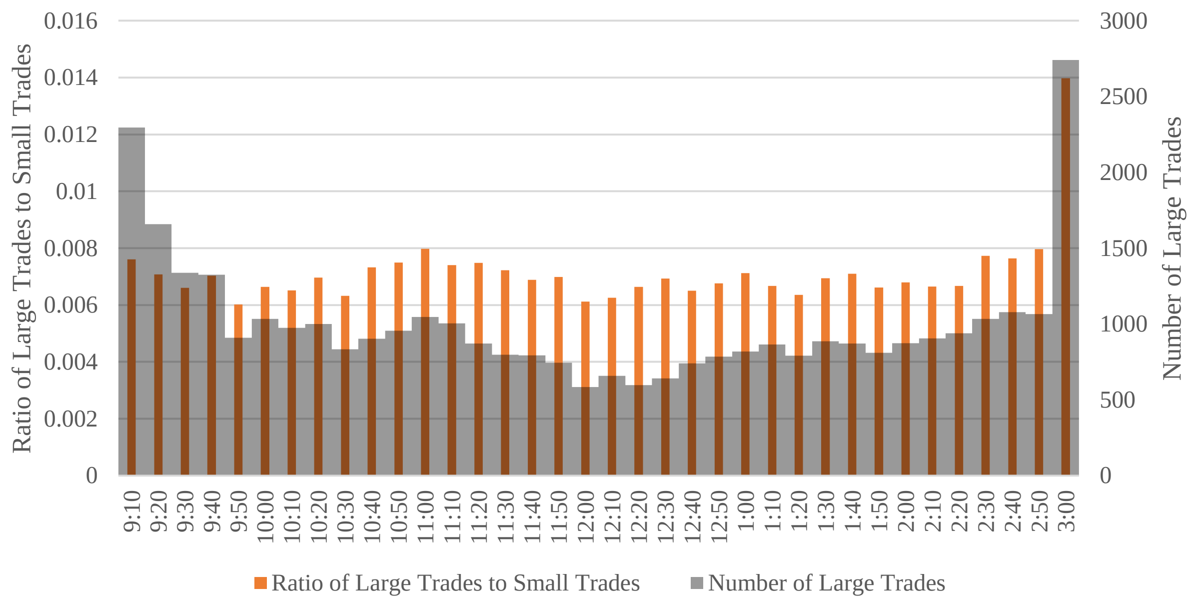
Panel A: Distribution of Large Trades Throughout the Trading Day



Panel B: Partial Autocorrelation Function of Large Trades

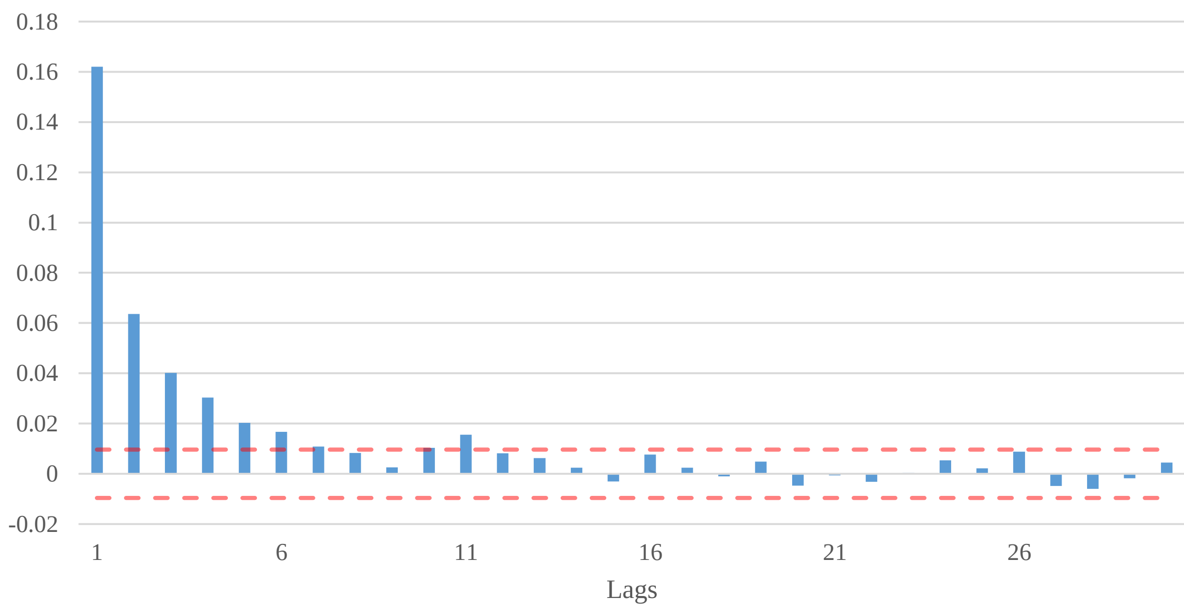
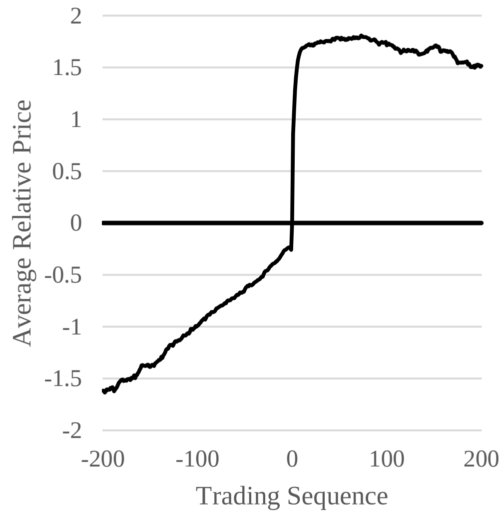


Figure 1 Characteristics of Large Trades: In Panel A we show the distribution of large trades throughout the trading day broken up by 10-minute increments beginning at 9:00 a.m. and ending at 3:00 p.m. Large trades are defined as those trades which occur in the top 1% of all trades by trade size. We plot the ratio of large trades to small trades across all trading days for each 10-minute increment on the left hand axis, and the total number of large trades which occur in each 10-minute increment across all trading days on the right hand axis. In Panel B we present the partial autocorrelation function for large trades for 30 lags. Values outside of the dotted lines are significant at the 5% level.

Panel A: Relative Price Changes Around a Large Buy



Panel B: Relative Price Changes Around a Large Sell

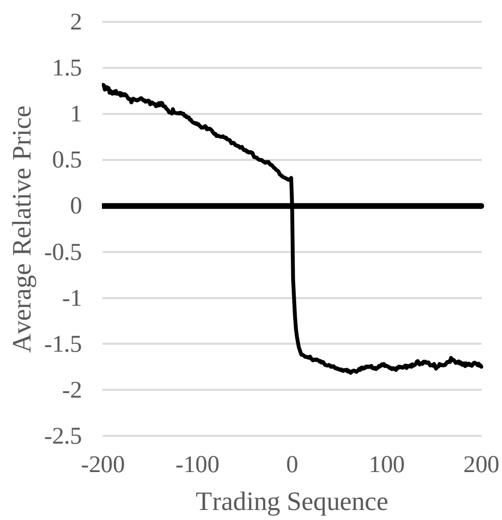


Figure 2: Relative Price Changes Around Large Trades. In this figure we present the average relative price changes around large trades. For each of the 32,303 large trades we begin measuring the relative price 200 trades before the arrival of the large trade. For each trade position $j \epsilon [-200{,}200]$ and each trade $i \epsilon [1, 36164]$ the relative price is computed as $p'(i,j) = \ln\left(\frac{p(i,j)}{p(i,0)}\right) * 10\text{^}4$ where $p(i,j)$ indicates the price at trade position j around large trade i and $p(i,0)$ indicates the price of the i^{th} large trade. For each trading position $j \epsilon [-200{,}200]$ we compute the average relative price across all trades as $\overline{p'(j)} = \frac{1}{N}\sum_{i=1}^{N} p'(i,j)$, where $N = 32{,}303$. This process is performed for buyer and seller-initiated trades separately. In Panel A we present the average relative price around the arrival of large buyer-initiated trades and in Panel B we present the average relative price around the arrival of large seller- initiated trades.

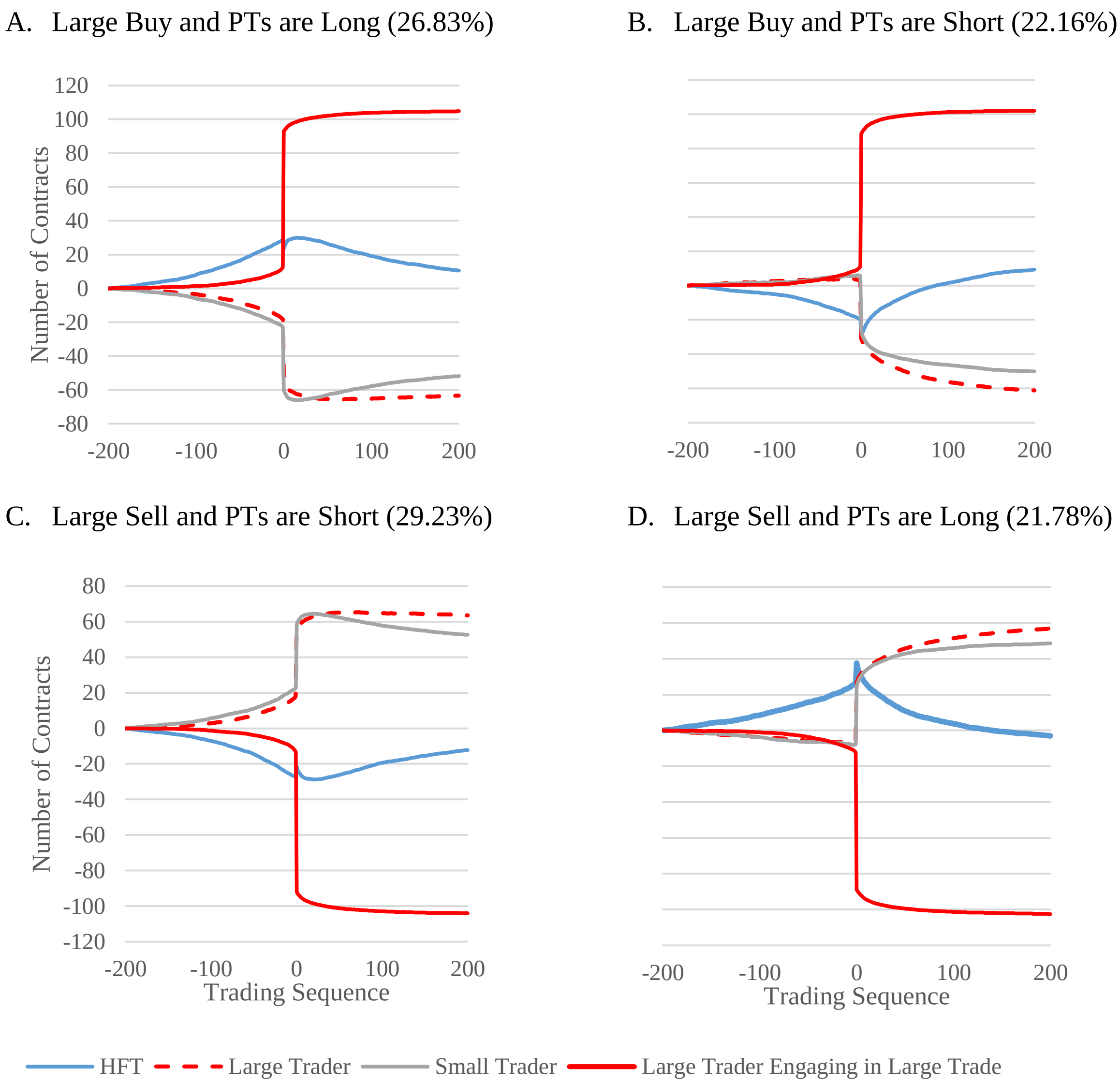


Figure 3 Trading Dynamics Around Large Trades. In this figure we plot trading dynamics for 200 trades before and after the arrival of large trades. Traders are classified as either PTs, small traders, large traders engaging in a given large trade, or large traders not engaging in a given large trade. All positions begin at zero at trade position $j = -200$, and for each trade position $j \epsilon [-200,200]$ and each trade $i \epsilon [1, 36164]$ we compute the aggregate position of the four trader types relative to their position at $j = -200$. For each relative trading position around the large trade $j \epsilon [-200,200]$ we then compute the average position in number of contracts of each of the four trader types across all large buyer and seller-initiated large trades separately. We then identify trades where PTs are on aggregate on the same side as the large trade and we further subdivide the sample of large trades into four groups based on whether the large trade is a buy or sell and whether or not PTs are on aggregate on the same side as the large trade. In Panel A we present the trading dynamics around the arrival of large buy orders when PTs are on the same side as the large order. In Panel B we present the trading dynamics around the arrival of large buy orders when PTs are on the opposite side as the large order. In Panel C we present the trading dynamics around the arrival of large sell orders when PTs are on the same side as the large order. In Panel D we present the trading dynamics around the arrival of large sell orders when PTs are on the opposite side as the large order.

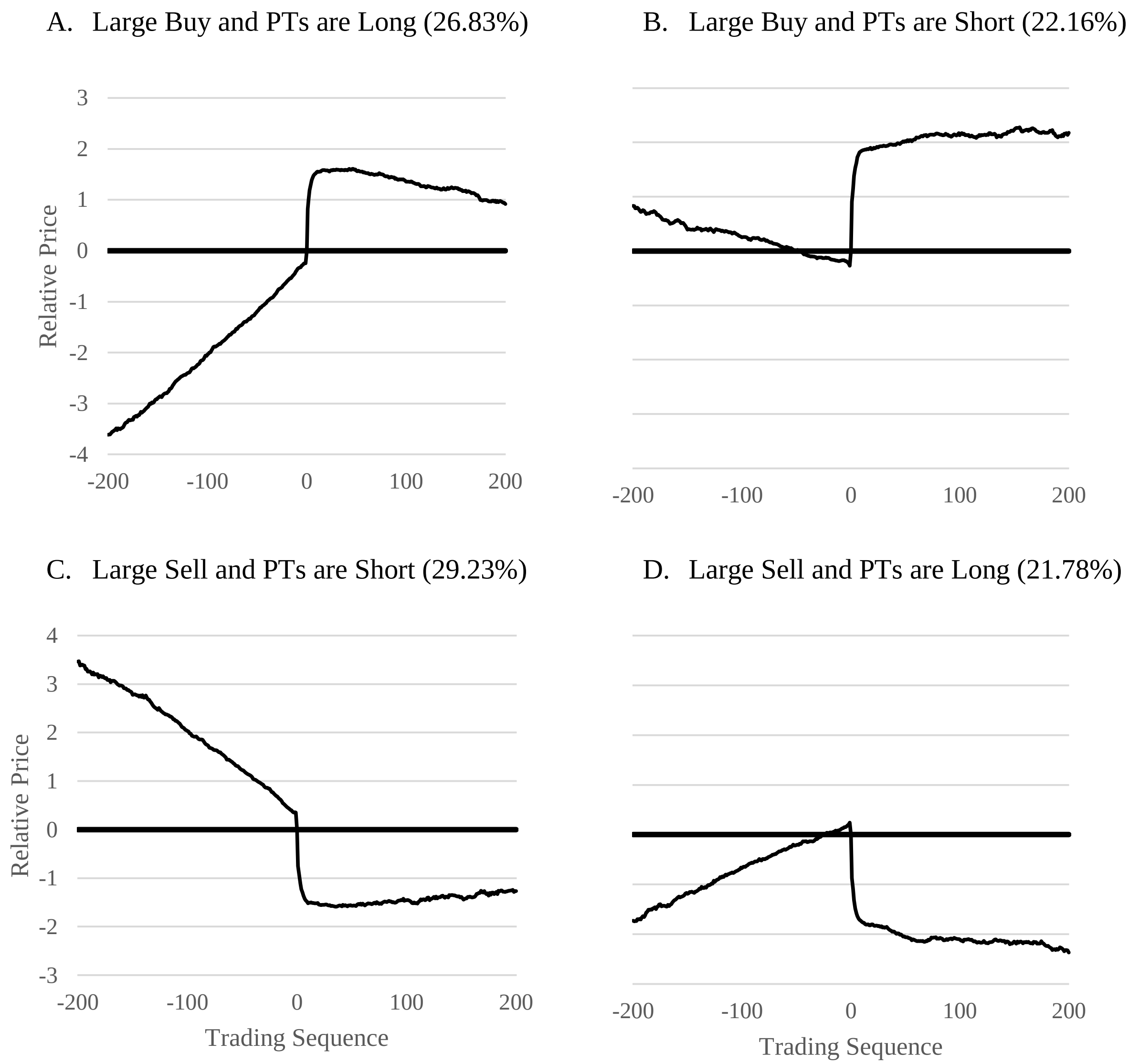


Figure 4: Relative Price Changes Around Large Trades. In this figure we plot average relative prices around the arrival of large buy and sell orders both for when the aggregate positions of PTs are on the same side as the large trade and when the aggregate positions of PTs are on the opposite side as the large trade. In Panels A and B we present the average relative price around the arrival of large buy orders when PTs are on the same and opposite side as the large order respectively. In Panels C and D we present the average relative price around the arrival of large sell orders when PTs are on the same and opposite side as the large order respectively. For each trade position $j \epsilon [-200,200]$ and each trade $i \epsilon [1, 36164]$ the relative price is computed as $p'(i,j) = \ln\left(\frac{p(i,j)}{p(i,0)}\right) * 10^{\wedge}4$ where $p(i,j)$ indicates the price at trade position j around large trade i and $p(i,0)$ indicates the price of the i^{th} large trade. For each trading position $j \epsilon [-200,200]$ we compute the average relative price across all trades as $\overline{p'(j)} = \frac{1}{N}\sum_{i=1}^{N} p'(i,j)$ where N is the number of large trades meeting a given criterion.

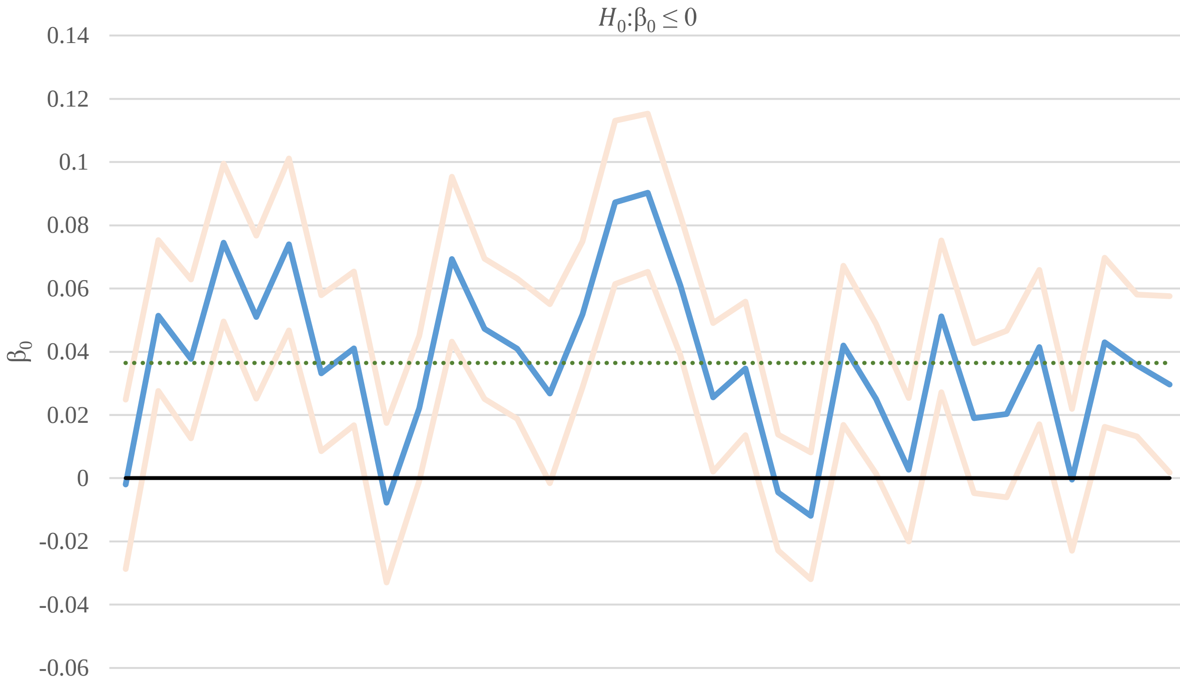


Figure 5 Time Series of β_0. This figure plots the time series of β_0 throughout the sample period. β_0 is estimated from the regression $Sign_i = \beta_0 SignPT_{k,i} + \sum_{j=1}^{15} \gamma_j Sign_{i-j} + \alpha_k + \varepsilon_i$ and indicate whether or not the 32 PTs in our sample build up positions on the same side as a large trade with a probability greater than random chance. $Sign_i$ is the sign of the i^{th}large trade and is equal to -1 for large seller-initiated trades and 1 for large buyer-initiated trades. We identify 32 accounts that trade in a manner consistent with the current literature associated with PTs and the variable $SignPT_{k,i}$ is the sign of the inventory accumulated by the k^{th} PT at the arrival of large trade i. Because large trades exhibit autocorrelation we include in our regression the sign of the prior 15 large trades. We also include fixed effects for each of the 32 PTs in our sample. We divide our 66-day sample into 33 two-day time periods and estimate the above regression for each two day sub-period separately and plot the estimated value of β_0 for each of the 33 sub-periods. The dotted line represents the mean value of β_0 across the sample while the solid blue line represents the evolution of β_0. We also include confidence intervals for β_0.

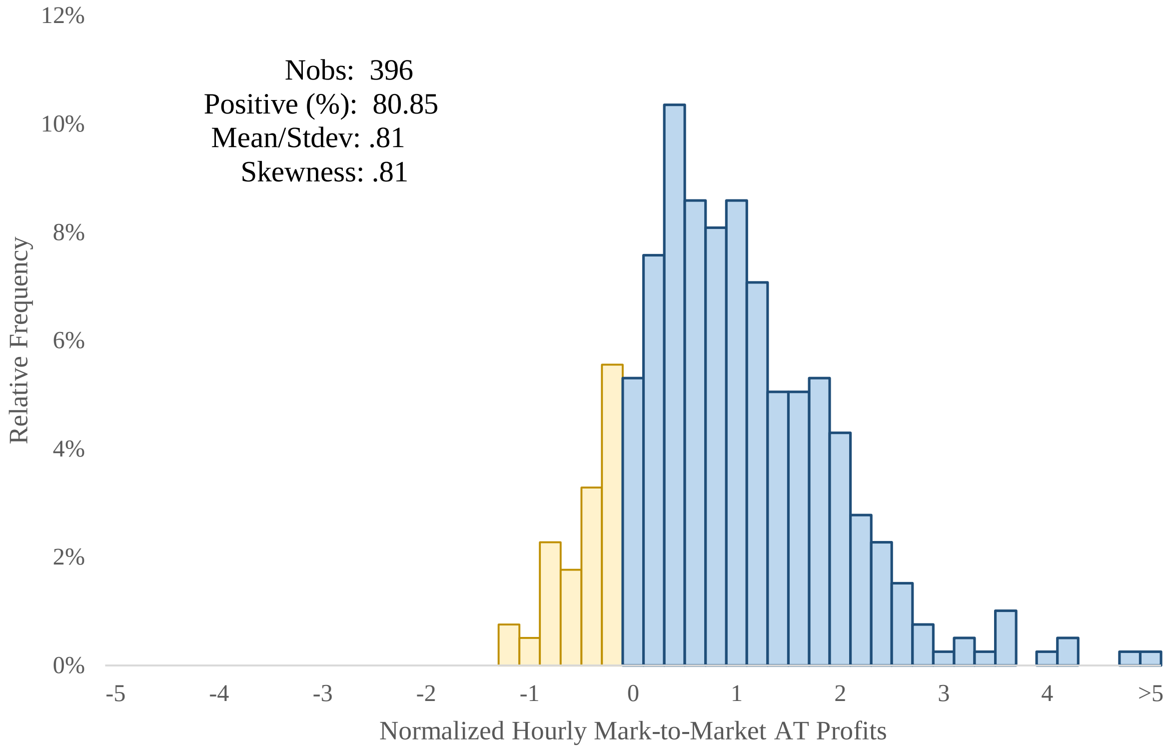


Figure 6: Normalized Hourly Mark-to-Market AT Profits. In this figure we present the histogram of aggregate hourly mark-to-market profits of the PTs in our sample. We divide our 66-day sample into 396 one hour segments representing the six trading hours of each of the 66 days in our sample. We impose that all PT positions are zero at the beginning of each 1-hour period. We then compute the profits and losses for PTs on all subsequent trades during that 1-hour period. At the end of the 1-hour period we liquidate any remaining PT positions at the current market price and we calculate the aggregate profits and losses for PTs during each 1-hour segment of our data. We normalize hourly profits by their standard deviation and plot a histogram of the relative frequencies of the 396 hourly mark-to-market profits in this figure.

Table 1: Characteristics of Large Trades

This table reports summary statistics for large trades. Large trades are defined as active trades by large traders which are among the largest 1% of all large trades. We identify 32,303 large trades in our sample. Large trades are defined as buyer-initiated if the large trader crossed the bid ask spread and bought at the ask price or seller-initiated if the large trader crossed the bid-ask spread and sold at the bid price. In our sample 48.99% of large trades are buyer-initiated and 51.01% of large trades are seller-initiated trades.

	Mean	Median	Std.	Max	Min
Large Trade Size	78.76	62.00	40.74	800.00	50.00
# of Large Trades per Day	547.94	531.00	109.30	951.00	334.00
Time Between Large Trades (sec)	39.97	16.31	65.17	1,239.29	0.01
Volume Between Large Trades	1,074.79	638.00	1,287.64	24,523.00	1.00
# of Trades Between Large Trades	489.33	281.00	612.58	11,253.00	1.00
# of Messages Between Large Trades	848.49	471.00	1,108.84	22,220.00	0.00

Table 2: Trading Characteristics of Account Types

This table presents descriptive statistics for the trader types in our data. Accounts are determined to be PTs if 1) average holding time for one position is less than 3 minutes, 2) average daily ratio of overnight inventories to contracts traded is less than 0.01%, and 3) the number of aggressive trades exceeds the number of passive trades. Large traders are defined as accounts that are not PTs which execute at least one trade that is among the top 1% of trades by size. Small traders are all other traders. In Panel A we provide statistics about the classifications of traders: foreign vs domestic and institutional vs retail. In Panel B we provide volume statistics for each of the three trader types. *Take* and *Make* indicate active and passive, and in Panel C we provide other statistics. These include *# of Switch/Day* which is defined as the number of times that a traders' inventory switches from positive to negative or from negative to positive, *Switch Time (sec)* which is measured as the time in seconds between when aggregate inventories switch in their direction, and *Overnight Ratio (%)* which is the ratio of inventory held overnight to daily trading volume.

Panel A: Trader Entity

	Total	Foreign	Institutional
Predatory Traders	32	5	24
Large Trader	737	179	557
Small Trader	24,403	391	3,057
Total	25,172	575	3,638

Panel B: Volume Ratio

	Total Volume		Large Trades		Small Trades	
	Take	Make	Take	Make	Take	Make
Predatory Traders	30.48	14.51	0.00	10.22	34.76	15.12
Large Trader	42.13	43.18	100.00	46.05	34.01	42.77
Small Trader	27.39	42.31	0.00	43.73	31.23	42.11
Daily Volume	348,114 (100%)		49,671 (14%)		298,443 (86%)	

Panel C: Other Statistics

	Mean	Median	Std.
# of Switch/Day			
Predatory Traders	91.10	58.53	92.83
Large Trader	5.09	1.45	18.67
Small Trader	4.32	2.16	10.00
Switch Time (sec)			
Predatory Traders	104.89	81.96	115.76
Large Trader	9,607.83	10,014.12	5,135.44
Small Trader	5,860.38	4,730.69	5,080.46
Overnight Ratio (%)			
Predatory Traders	0.00	0.00	0.02
Large Trader	40.33	29.80	36.47
Small Trader	21.40	4.44	32.86

Table 3: Conditional Regression Results

In Panel A of this table we use three variations of the model

$$Sign_i = \beta_0 SignPT_{k,i} + \sum_{j=1}^{15} \gamma_j Sign_{i-j} + \alpha_k + \varepsilon_i$$

to test the hypothesis that PTs are on the right side of large trades with greater than 50% probability. $Sign_i$ is the sign of the i^{th} large trade and is equal to -1 for large sells and 1 for large buys. $SignPT_{k,i}$ as the sign of the k^{th} PT's inventory at the time of the i^{th}large trade and is either 1 or -1 indicating whether or not the k^{th} PT was long or short at the time of the i^{th} large trade respectively, and α_k is an PT specific intercept. In model (1) we do not include PT fixed effects or the values for the lagged sign of the large trades, in model (2) we include PT fixed effects, but not the lagged signs of the prior large trades, in model (3) we estimate the full model. In Panel B we present the results from a related regression below.

$$Size_i * Sign_i = \beta_0 Size_{k,i} * SignPT_{k,i} + \sum_{j=1}^{15} \gamma_j Size_{i-j} * Sign_{i-j} + \alpha_k + \varepsilon_i$$

The only modification from the model used in Panel A is that we multiply $Sign_i$ by the size in contracts of the i^{th} large trade and $SignPT_{k,i}$ by the size of PT k's position at the time that the i^{th} large order arrives. Similar to Panel A, in model (4) we do not include PT fixed effects or the values for the lagged sign of the large trades, in model (5) we include PT fixed effects, but not the lagged signs of the prior large trades, in model (6) we estimate the full model. We do not include stars because all estimates are significant at the 1% level.

Model		Estimate	S.E.	t value	p value	Adj.R^2
	Panel A: Direction of Trade and Position					
(1) Simple OLS	$SignPT_{k,i}$	0.063	0.002	29.493	0.000	0.004
(2) Fixed Effect	$SignPT_{k,i}$	0.064	0.002	29.617	0.000	0.004
(3) Fixed Effect + Lag $Sign_i$	$SignPT_{k,i}$	0.036	0.002	16.766	0.000	0.041
	Panel B: Direction*Size of Trade and Position					
(4) Simple OLS	$Size_{k,i} * SignPT_{k,i}$	0.085	0.003	29.112	0.000	0.004
(5) Fixed Effect	$Size_{k,i} * SignPT_{k,i}$	0.085	0.003	29.092	0.000	0.004
(6) Fixed Effect +Lag $Size_i * Sign_i$	$Size_{k,i} * SignPT_{k,i}$	0.050	0.003	17.150	0.000	0.040

Table 4: Unconditional Regression Results

In this table we test the unconditional hypothesis that PT inventories predict the aggregate direction of large trades with greater than random chance. For this analysis we divide our sample into 120 second segments and for each 120 second segment we compute $y_{(t,t+1]}$ as number of buyer-initiated large trades minus the number of seller-initiated large trades which arrive during time segment t to $t+1$. We also calculate x_t as the sign of the aggregate inventory position of PTs at time t, and $x_{(t-i,t-i+1]}$ is the sign of PT's net trades between time segment $t-i$ and $t-i+1$. We then use the regression model

$$y_{(t,t+1]} = \beta_0 + \beta_1 x_t + \sum_{i=1}^{5} \beta_{i+1} x_{(t-i,t-i+1]} + \varepsilon_{(t,t+1]}$$

to determine if PT inventories at time t predict the net direction of large trades which arrive between time t and t+1. In Panel B we perform the same analysis as in Panel A except that we use the net size of large trades multiplied by the sign of aggregate large trades, and the aggregate size of PT positions at time t multiplied by the sign of PT positions. Autocorrelation in the residuals is controlled by employing the Newey and West (1994) methodology with 30 lags. One, two, and three stars represent significance at the 10, 5, and 1% levels respectively.

	Panel A: Direction			Panel B: Direction * Size		
	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.06**	-0.06**	-0.06**	-2.94	-3.15	-2.94
	(2.57)	(2.44)	(2.54)	(1.34)	(1.4)	(1.34)
x_t	0.17***		0.16***	0.21***		0.22***
	(7.49)		(6.04)	(7.5)		(3.7)
$x_{(t-1,t]}$		0.09***	0.01		0.16***	-0.02
		(3.9)	(0.34)		(6.42)	(0.28)
$x_{(t-2,t-1]}$		0.09***	0.05*		0.17***	0.03
		(3.3)	(1.83)		(5.47)	(0.51)
$x_{(t-3,t-2]}$		0.05*	0.03		0.14***	0.03
		(1.83)	(1.12)		(4.23)	(0.6)
$x_{(t-4,t-3]}$		0.03	0.02		0.06*	-0.02
		(1.18)	(0.82)		(1.88)	(0.6)
$x_{(t-5,t-4]}$		-0.02	-0.02		0.01	-0.03
		(0.75)	(0.97)		(0.48)	(1.11)
Nobs	11,674	11,674	11,674	11,674	11,674	11,674
Adj.R^2	0.0049	0.0017	0.0050	0.0056	0.0043	0.0057

Table 5: Unconditional Regression Results with Varying Time

In this table we test the unconditional hypothesis that PT inventories predict the aggregate direction of large trades with greater than random chance. For this analysis we divide our sample into segments of varying time length and for each segment we compute $y_{(t,t+1]}$ as number of buyer-initiated large trades minus the number of seller-initiated large trades which arrive during time segment t to $t+1$. We also calculate x_t as the sign of the aggregate inventory position of PTs at time t, and $x_{(t-i,t-i+1]}$ is the sign of PT's net trades between time $t-i$ and $t-i+1$. We then use the regression model

$$y_{(t,t+1]} = \beta_0 + \beta_1 x_t + \sum_{i=1}^{5} \beta_{i+1} x_{(t-i,t-i+1]} + \varepsilon_{(t,t+1]}$$

to determine if PT inventories predict the arrival of large trades for time segments ranging from 5 seconds to 240 seconds. Autocorrelation in the residuals is controlled by employing the Newey and West (1994) methodology with 30 lags. One, two, and three stars represent significance at the 10, 5, and 1% levels respectively.

	Panel A. Direction: $y_{(t,t+1]}$					
	5sec	20sec	40sec	60sec	120sec	240sec
Intercept	-0.00***	-0.01**	-0.02**	-0.03**	-0.06**	-0.13***
	(-2.68)	(-2.45)	(-2.47)	(-2.49)	(-2.54)	(-2.61)
x_t	0.01***	0.04***	0.08***	0.10***	0.16***	0.26***
	(12.89)	(11.45)	(9.42)	(8.01)	(6.04)	(4.42)
$x_{(t-1,t]}$	0.00	0.00	0.00	-0.02*	0.01	0.00
	(0.13)	(0.47)	(0.04)	(-1.9)	(0.34)	(0.04)
$x_{(t-2,t-1]}$	0.00**	0.01*	0.00	0.01	0.05*	-0.03
	(2.42)	(1.92)	(0.28)	(0.45)	(1.83)	(-0.61)
$x_{(t-3,t-2]}$	0.00*	0.01**	0.00	0.02	0.03	-0.01
	(1.91)	(2.57)	(0.27)	(1.63)	(1.12)	(-0.24)
$x_{(t-4,t-3]}$	0.00	0.00	0.01	0.01	0.02	-0.04
	(0.78)	(0.73)	(1.54)	(0.47)	(0.82)	(0.64)
$x_{(t-5,t-4]}$	0.00***	0.01*	0.01*	0.01	-0.02	0.03
	(3.73)	(1.8)	(1.95)	(1.13)	(-0.97)	(0.53)
Nobs	283,093	71,819	35,749	23,683	11,674	5,672
Adj.R^2	0.0009	0.0026	0.0036	0.0034	0.0050	0.0045

Table 6: Regression Results for Effect of Child Size and Speed

In this table we test separately and jointly the hypothesis that the size of the child orders preceding the large trade and the speed of the large trader affect the probability of being front-run, using the model

$$Sign_i = \beta_0 + \beta_1 SignPT_{k,i} + \beta_2 SignPT_{k,i} * Child_i + \beta_3 SignPT_{k,i} * \ Speed_i + \beta_4 SignPT_{k,i} * Child_i * Speed_i + \sum_{j=1}^{15} \gamma_j Sign_{i-j} + \alpha_k + \varepsilon_i$$

$Sign_i$ is the sign of the i^{th} large trade and is equal to -1 for large sells and 1 for large buys. $SignPT_{k,i}$ as the sign of the k^{th} PT's inventory at the time of the i^{th}large trade and is either 1 or -1, indicating whether or not the k^{th} PT was long or short at the time of the i^{th}large trade respectively, and α_k is a PT specific intercept. For each large trade i we calculate the average trade size for all trades executed by the given large trader beginning at large trade $(i - 3)$ and ending just before large trade i. We sort all large trades by their corresponding average child order size and identify those large trades with child order sizes in the top 50% of child order sizes as having large child orders. For large trades associated with larger than average child order sizes, the variable $Child_i = 1$ otherwise it equals 0. We calculate speed for each of the 737 large traders in our sample as the average difference in time between order submission and order fulfillment for all passive orders that a large trader executes in our sample. We then sort large traders by average execution speed and those large traders in the slowest 50% of large traders are identified as being slow large traders and for large trades associated with these slow traders the variable $Speed_i = 1$ otherwise it equals 0. In model (1) we omit the interaction of speed and PT position, and speed and child order size to test the hypothesis that large trades associated with large child orders are more likely to be front-run. In model (2) we omit the interaction of child order size and PT positon, and speed and child order size to test the hypothesis that large trades executed by slow large traders are more likely to be front-run. In model (3) we estimate the full model with tests the joint hypothesis that both child order size and speed impact the likelihood that a large order will be successfully front-run. We do not include stars because all estimates are significant at the 1% level.

		Estimate	S.E.	t value	Pr($\leq \lvert t \rvert$)	Adj.R^2
(1) Child Size	$SignPT_{k,i}$	-0.019	0.003	-6.392	0.000	
	$SignPT_{k,i} * Child_i$	0.110	0.004	26.183	0.000	0.043
(2) Speed	$SignPT_{k,i}$	0.021	0.003	6.684	0.000	
	$SignPT_{k,i} * \ Speed_i$	0.026	0.004	6.253	0.000	0.041
(3) Child Size + Speed	$SignPT_{k,i}$	-0.031	0.005	-6.103	0.000	
	$SignPT_{k,i} * \ Speed_i$	0.018	0.006	2.879	0.004	
	$SignPT_{k,i} * Child_i$	0.086	0.006	13.318	0.000	0.044
	$SignPT_{k,i} * Child_i * Speed_i$	0.059	0.009	6.909	0.000	

Table 7: Vector Autoregression Results

In this table we use a vector autoregression to model the dynamic relation between price changes and the trading activity of predatory traders, large traders, and small traders. We use the following VAR model to understand the dynamics.

$$X_t = \gamma_0 + \Lambda_t + \sum_{i=1}^{5} \Gamma'_i X_{t-i}$$

X_t is a 4x1 column vector containing the time t values of $\Delta p_{t,t+1}$, $\mathrm{PT}_{t,t+1}$, $Large_{t,t+1}$, and $Small_{t,t+1}$. $\Delta p_{t,t+1} = \ln\left(\frac{p_{t+1}}{p_t}\right) * 10^4$, where p_t is the price at the t^{th} large trade. We also define $Large_{t,t+1}$, $PT_{t,t+1}$, and $Small_{t,t+1}$ as the net signed active trades of large traders, predatory, and small traders respectively between the t^{th} and the $(t+1)^{th}$ large trade. The matrix Λ_t is a 4x1 column vector with $\lambda_{12} Large_{t,t+1} + \lambda_{13} HFT_{t,t+1} + \lambda_{14} Small_{t,t+1}$, in the first row, and all other entries equal to zero. Γ_i is a 4x4 vector of coefficients, and $X_{t-i}$is a 4x1 column vector with lagged values of $\Delta p_{t,t+1}$, $\mathrm{PT}_{t,t+1}$, $Large_{t,t+1}$, and $Small_{t,t+1}$ in rows 1,2,3, and 4 respectively. In panel A we only show the results for the coefficients from the VAR analysis which relate to innovations in price for 4 permutations of our base model. In panel B we present coefficients for all coefficients from our baseline VAR. One, two, and three stars represent significance at the 10, 5, and 1% levels respectively. t-statistics in parantheses.

Panel A: Trading Impact on Price Changes

	(1) $\Delta p_{t,t+1}$		(2) $\Delta p_{t,t+1}$		(3) $\Delta p_{t,t+1}$		(4) $\Delta p_{t,t+1}$	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
$PT_{t,t+1}$	-0.015***	(-3.36)	0.019***	(4.36)	0.01**	(2.25)	-0.025***	(-5.52)
$Large_{t,t+1}$	0.095***	(50.52)					0.091***	(50.24)
$Small_{t,t+1}$	-0.035***	(-8.59)			0.028***	(6.83)		
$PT_{t-1,t}$	0.00	(-0.09)	0.021***	(4.63)	0.016***	(3.42)	-0.006	(-1.28)
$PT_{t-2,t-1}$	-0.002	(-0.45)	0.016***	(3.44)	0.013***	(2.81)	-0.005	(-1.02)
$PT_{t-3,t-2}$	-0.008*	(-1.71)	0.007	(1.53)	0.005	(0.99)	-0.01**	(-2.21)
$PT_{t-4,t-3}$	-0.006	(-1.43)	0.003	(0.72)	0.002	(0.45)	-0.007*	(-1.65)
$PT_{t-5,t-4}$	-0.004	(-0.93)	0.003	(0.64)	0.002	(0.47)	-0.005	(-1.05)
$Large_{t-1,t}$	0.003	(1.64)	0.012***	(6.04)	0.01***	(5.55)	0.003	(1.28)
$Large_{t-2,t-1}$	0.005***	(2.71)	0.011***	(5.31)	0.01***	(4.99)	0.005**	(2.47)
$Large_{t-3,t-2}$	0.00	(-0.15)	0.002	(0.84)	0.001	(0.71)	-0.001	(-0.26)
$Large_{t-4,t-3}$	0.001	(0.66)	0.003	(1.56)	0.003	(1.44)	0.001	(0.55)
$Large_{t-5,t-4}$	0.002	(0.82)	0.004**	(2.2)	0.004**	(2.05)	0.001	(0.7)
$Small_{t-1,t}$	0.004	(1.02)	0.002	(0.56)	0.00	(0.01)	0.001	(0.31)
$Small_{t-2,t-1}$	0.003	(0.68)	0.005	(1.08)	0.003	(0.64)	0.001	(0.15)
$Small_{t-3,t-2}$	0.002	(0.55)	0.006	(1.45)	0.005	(1.09)	0.001	(0.15)
$Small_{t-4,t-3}$	0.009**	(2.17)	0.013***	(3.06)	0.011***	(2.72)	0.007*	(1.8)
$Small_{t-5,t-4}$	-0.005	(-1.12)	-0.002	(-0.45)	-0.003	(-0.77)	-0.006	(-1.48)
$\Delta p_{t-1,t}$	0.027***	(5.12)	0.029***	(5.29)	0.029***	(5.3)	0.027***	(5.13)
$\Delta p_{t-2,t-1}$	-0.005	(-0.9)	-0.005	(-0.86)	-0.005	(-0.86)	-0.005	(-0.89)
$\Delta p_{t-3,t-2}$	0.018***	(3.41)	0.021***	(3.85)	0.021***	(3.86)	0.018***	(3.45)
$\Delta p_{t-4,t-3}$	0.018***	(3.37)	0.02***	(3.59)	0.02***	(3.58)	0.018***	(3.37)
$\Delta p_{t-5,t-4}$	0.004	(0.74)	0.002	(0.37)	0.002	(0.38)	0.004	(0.74)
Nobs	35,438		35,438		35,438		35,438	
Adj.R^2	0.08		0.01		0.01		0.08	

Panel B: Full VAR model

	(1) $\Delta p_{t,t+1}$		(2) $PT_{t,t+1}$		(3) $Large_{t,t+1}$		(4) $Small_{t,t+1}$	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
$PT_{t,t+1}$	-0.015***	(-3.36)						
$Large_{t,t+1}$	0.095***	(50.52)						
$Small_{t,t+1}$	-0.035***	(-8.59)						
$PT_{t-1,t}$	0.00	(-0.09)	-0.115***	(-20.75)	0.244***	(18.35)	0.157***	(25.03)
$PT_{t-2,t-1}$	-0.002	(-0.45)	-0.092***	(-16.18)	0.185***	(13.66)	0.075***	(11.8)
$PT_{t-3,t-2}$	-0.008*	(-1.71)	-0.074***	(-13.02)	0.155***	(11.42)	0.068***	(10.64)
$PT_{t-4,t-3}$	-0.006	(-1.43)	-0.06***	(-10.69)	0.09***	(6.7)	0.026***	(4.15)
$PT_{t-5,t-4}$	-0.004	(-0.93)	-0.038***	(-6.96)	0.064***	(4.89)	0.014**	(2.33)
$Large_{t-1,t}$	0.003	(1.64)	0.01***	(4.04)	0.112***	(19)	0.038***	(13.67)
$Large_{t-2,t-1}$	0.005***	(2.71)	0.003	(1.04)	0.067***	(11.3)	0.024***	(8.51)
$Large_{t-3,t-2}$	0.00	(-0.15)	-0.001	(-0.28)	0.024***	(4.09)	0.009***	(3.34)
$Large_{t-4,t-3}$	0.001	(0.66)	-0.004	(-1.6)	0.021***	(3.59)	0.008***	(2.85)
$Large_{t-5,t-4}$	0.002	(0.82)	-0.004	(-1.44)	0.033***	(5.51)	0.01***	(3.73)
$Small_{t-1,t}$	0.004	(1.02)	-0.019***	(-3.65)	0.003	(0.24)	0.078***	(13.43)
$Small_{t-2,t-1}$	0.003	(0.68)	-0.005	(-1)	0.041***	(3.36)	0.066***	(11.4)
$Small_{t-3,t-2}$	0.002	(0.55)	-0.022***	(-4.33)	0.05***	(4.1)	0.048***	(8.19)
$Small_{t-4,t-3}$	0.009**	(2.17)	-0.015***	(-2.95)	0.055***	(4.45)	0.047***	(8.11)
$Small_{t-5,t-4}$	-0.005	(-1.12)	-0.018***	(-3.55)	0.037***	(3.03)	0.042***	(7.35)
$\Delta p_{t-1,t}$	0.027***	(5.12)	0.188	(0.28)	2.102	(1.32)	0.013	(0.02)
$\Delta p_{t-2,t-1}$	-0.005	(-0.9)	-1.332**	(-2)	-0.624	(-0.39)	-0.445	(-0.59)
$\Delta p_{t-3,t-2}$	0.018***	(3.41)	-0.18	(-0.27)	3.049*	(1.92)	-0.161	(-0.22)
$\Delta p_{t-4,t-3}$	0.018***	(3.37)	-0.041	(-0.06)	2.026	(1.28)	0.325	(0.43)
$\Delta p_{t-5,t-4}$	0.004	(0.74)	-0.061	(-0.09)	-2.139	(-1.35)	-0.366	(-0.49)
Nobs	35,438		35,438		35,438		35,438	
Adj.R^2	0.08		0.03		0.06		0.09	