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ABSTRACT

We characterize the behavior of individual retail traders in futures markets using newly available data on overnight positions and required margins. Individual participants typically only appear for a handful of trades(median 4 trades lasting 4 days each) and have gains or losses of a few hundred dollars per trading event. Retail traders generally follow a contrarian strategy and enter long (short) positions when the contract price declines (rises). In contrast to conventional wisdom that retail is biased toward long positions, traders enter into short contracts in similar amounts as long contracts. We find evidence that larger dollar losses on the first trade is significantly associated with leaving the market permanently.

JEL classification: G12, G19

Keywords:Retail traders, Futures, Margins

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I. Introduction

Retail traders and their trading activity has seen continuing growth within the last 5 - 10 years (Gurrola-Perez, Kaitao and Bill (2022)). Recent data reports retail trader activity to be around \$1.4 billion per day on average in the U.S. equity markets.[1] However, all this increased activity also meant that regulators have been worried about the trading patterns of retail traders and whether there should be limitations to retail trading.[2] Academics have also shown interest in this topic and produced a number of studies analyzing retail traders, however most of those were focused on the retail traders in the equity market (Jones et al. (2023); Ben-David and Hirshleifer (2012); Boehmer et al. (2021); Odean (1998)).

In this paper we add to the existing literature by characterizing the behavior of individual retail traders in futures markets using newly available data on overnight positions and required margins. This regulatory data-set allows us to identify 36,538 retail traders holding contracts whose positions we track in 50 different futures markets(February 2021 to November 2022). A typical retail trader in our sample engages with futures markets by moving in and out of a single contract over the course of several weeks and holding the contract for a only a few days at a time. The median trader in our sample has 4 distinct trading events(defined as consecutive days with a position) and trades 2 different markets over the sample period. Retail traders frequently hold micro equity index contracts with relatively small margin requirements such as the Micro E-Mini S&P or the Micro NASDAQ 100. [3]

[1] See https://www.reuters.com/business/retail-consumer/retail-traders-pile-into-us-stocks-focus-shifts-evs-ai-2023-07-06/

[2] See https://www.cnbc.com/2022/03/28/regulators-are-worried-that-retail-traders-are-getting-in-over-their-heads.html and https://www.marketsmedia.com/german-regulator-seeks-to-ban-retail-futures-trading/

[3] We realize that some of these findings are jointly decided with our retail trader identification strategy.

In general, we find that retail traders lose money in futures markets. The median trader in our sample has estimated losses in the range of \$100 - \$200 depending on how many events they trade in. Traders in the 60$^{\text{th}}$ percentile of the P&L distribution break even. The overall distribution has a left skew with losses on these retail positions being overall greater than the gains by retail traders and are measured in thousands of dollars. Importantly, we find evidence that larger dollar losses on the first trade is significantly associated with leaving the market permanently.

Focusing on retail traders' decision to participate in the futures market, we see that they tend to act like contrarians when they enter the market, getting long (short) when the contract price declines (rises). They exit at higher than usual levels when the price moves against them. We do not find a preference for going long or short within retail traders, as participants entered on the short side nearly as often on the long side.

Our findings partially confirm the "trade to learn" hypothesis (Linnainmaa (2011)). Investors may trade even if they expect to lose money in order to learn whether or not they are skilled. Traders who receive a negative signal through losses in their initial set of trades will permanently exit the market. Empirically, our findings support these theoretical predictions, but only for a subset of our traders. While many traders exit the market after large initial losses, we also observe that traders in the bottom quintile of initial performance continue to trade as frequently as those in the top quintile.

Mahani and Bernhardt (2007) presents a theoretical model where individual speculators do not know their abilities, but they learn about them through an overlapping generations environment. Traders who learn about their skill through past performance may increase their trading intensity(i.e. trade frequency and trade size). Empirically, we observe this at the tails of our profit distribution; traders who lose big in their first set of trades chose to cease trading, and traders who win big in their first set of trades continue trading and winning. However, we also show that trader's performance during their first few trades is not strongly associated with the intensity of their future trades, if the gains or losses from their initial trades are not sizable.

While the research on retail traders has had a resurgence within the last few years, the earliest research on this topic goes back to 1949 (Stewart (1949)), where the main takeaway is that retail traders lose money on average. With respect to retail traders in futures markets, Draper (1985) offers analysis of a rich survey data, even presenting demographic information on what they call small public traders.

Most of the recent literature on retail traders focuses their analysis on stock trading by retail traders and show that retail traders lose money overall (Jones et al. (2023); Ben-David and Hirshleifer (2012)). Another strand of recent literature focuses on options trading by retail investors (De Silva, So and Smith (2022); Bryzgalova, Pavlova and Sikorskaya (2022); Eaton et al. (2022)) and they also find that retail traders make poor bets, invest in riskier options, and that market volatility is lower when they are not trading.

One explanation for why retail traders might be losing money, on average, comes from the theoretical model by (Barber, Lin and Odean 2023), where retail traders in their model, unlike professional traders, receive a low precision signal. The retails traders who have higher overconfidence are more likely to use margin, trade more frequently, and lose more in their model. Another potential explanation for our findings could be that retail traders lack financial literacy. (Lusardi and Mitchell 2011) shows that financial literacy is correlated with important financial behaviors, and (Anderson, Baker and Robinson 2017) show that perceived literacy motivates behavior, rather than actual literacy.

While our data do not allow us to directly observe traders' overconfidence or financial literacy, by focusing on retail traders active in the futures markets which allow for leveraged trading, we believe we are capturing traders that are with more than average overconfidence. Additionally, the retail traders we focus on trade predominantly in futures but not options, which might point to a lower than average financial literacy.

The paper is organized as follows. Section II explains how we define retail traders in our data and presents basics statistics on their distribution. Section III provides information on trading behavior and trading positions of retails traders. Section IV explains our methodology for measuring profit and loss (P&L) of retail traders and presents their P&L statistics. In Section V we provide analysis on futures market entry and exit decisions of retail traders, and in Section VI we offer our concluding remarks.

II. Data

The primary data source is a regulatory dataset on margin account positions reported to the Commodity Futures Trading Commission (CFTC). On each date in the sample (February 2021 to November 2022), we observe end-of-day information on each customer account's futures positions, including options on futures. We observe whether a given position is long or short, the quantity of contracts held, the expiry month of the contracts, and the settlement price of the contract, as well as a name associated with each customer account. The data also include the required margin amount, for that day, associated with the account. Our focus is on the Chicago Mercantile Exchange positions reported to the CFTC, and we further refine our sample to accounts held by a large futures commission merchant widely understood to have a large amount of retail individuals as customers.

A. Defining a Retail Trader

Our data does not have a classification field for the traders, so we are forced to introduce our own retail trader definition. To that effect, we further refine the data-set using the account identifier information. This information is limited to the character string linked with the positions and margin information; this data source has no other demographic information on the accounts. We first filter out accounts that are likely to be institutional, such as financial firms, agricultural entities, or have other indicia of a "business" rather than a natural person trading on a personal, financial account. We therefore exclude accounts that are likely to be financial firms by excluding identifiers including words such as capital, fund, investment, trading, retirement, or series. Agricultural enterprises (which are likely to be engaged in hedging activities associated with physical agricultural commodities) are filtered by excluding accounts with identifiers including words such as farm, ranch, grain, and co-op. Finally, we exclude accounts with identifiers including strings such as INC, CO, LLC, and LLP. We do not incorporate omnibus accounts, which aggregate positions held, for example, by customers of another broker who is not a clearing member. Because such accounts commingle the positions of many distinct, customer-level accounts, they are not informative for the purposes of our analysis.[4]

Finally, we use filters associated with the margin information and position information to screen out a modest number of large accounts, positions in the most inactive contracts, and accounts that hold only option positions. In order to focus on small, retail investors, we eliminate accounts that ever had more than $50,000 in initial margin at any point during our sample period. We also focus on the 50 most active contracts traded, and we conduct our analysis only on futures positions.

B. Statistics on Retail Traders

How restrictive is our $50,000 margin cutoff used to identify retail traders? In Figure 1, we present the frequency of the average margin required, across the days in our sample, by individual traders. It illustrates that most of the accounts in the sample typically have margin requirements measured in the hundreds of dollars or in single-digit thousands.

[4] A full list of the words we use to exclude non-retail traders can be found in the Appendix.

More importantly, the frequency of observation dips down to very low levels past $10,000 margin, which means very few (and very large) accounts are left out with the our $50,000 margin cutoff.

Table I provides more precise cutoffs of the same distribution. The median account had a required margin of $3,840, and the account size does not meaningfully approach the $50,000 cut-off, even for the largest accounts in the sample. We observe that 95% of the accounts had an average margin below $20,000. In the same table we also present margin calculations *by event*, which identifies occasions when a trader is holding position in a contract for a consecutive number of days. Even for the distribution of margins held for extended periods, we find that 99% of traders held margin that is below $32,000. It is readily apparent that these accounts are not putting tens of thousands of dollars at risk overnight.

Which futures markets do retails traders invest in? Table II reports the most frequently held markets by our retail sample. We sample one day (day 15 of the month as long as it is a trading day) from each month and measure how many retail traders hold positions in each market. That gives us 20 observations for each market and we use the median of those observations to come up with a number of traders statistic for each market. Retail positions are highly concentrated in a handful of markets. Over these ten markets, we see a sharp drop-off in the average number of accounts holding the contract. The top two contracts (both broad-based equity indexes) each average over 1,000 account holders, while the 10^{th} most widely held contract averages 176 accounts. Our sample of analysis extends to the 50th most widely held contract, with an median of 34 accounts reporting positions. Therefore, the focus on the top 50 markets is not a driver of the results.

Moreover, the table highlights the type of contract held by these traders, with a clear theme emerging: they tend to hold micro contracts on benchmark financial instruments.

The micro contracts are a relatively recent introduction and feature a notional size that is 1/10 of the standard, e-mini contract size. For example, the e-mini S&P 500 contract has a contract unit of $50 times the level of the S&P index, whereas the micro e-mini S&P 500 contract has a contract unit of $5 times the index level. Correspondingly, the required margin for the micro contracts is also smaller. During the sample, the required margin for the e-mini S&P had an order of magnitude of $10,000, while the micro contract featured a required margin on the order of $1,000.[5]

Our final sample covers 36,538 distinct retail accounts during this period. Figure 2 shows the number of daily accounts in our sample at our retail brokerage. While there is quite a turnover in the retail traders active in the market from one period to another, a typical day in the sample has 7,000-8,000 active accounts. The beginning and the end of our sample seems to experience a relatively higher number of traders active in the market, however we do not think this is driven by any major change in the futures market overall.

III. Description of Retail Traders

A. Trading Behavior

Rather than following a long-term buy-and-hold strategy, retail trading in futures markets tends to consist of multiple distinct trading events where each event lasts for a few days. The typical trader in our sample is in and out of futures markets 4 different times (with some breaks in between). These individual investment episodes, which we call events, are generally short with half of the events lasting 4 days or less with traders waiting a week before re-entering the futures market.

[5]We present statistics on the percentage of total open interest held by the retail traders in the Appendix.

As described in the previous section, we see traders' end-of-day positions and margins. This means if a trader suddenly shows up with a position in our data on day t, then we know they entered into that position sometime that day. If the same trader holds that position on days $t+1$ and $t+2$, but we do not observe any position for that trader in that contract on day $t+3$, that indicates the trader got out of the market sometime on day $t+3$, bringing her total number of days with position up to 4 and we record this event as lasting 4 days.[6]

Table III reports the summary statistics for how traders move in and out of the futures markets. First interesting observation is that approximately 20% of traders are in the market just a single time, meaning only one number of event is observed for them. At the other end of the distribution, we see 10% of the traders having 20 or more distinct trading events over the sample period. The second column in the table reports the total number of days that those traders were in the market across individual trading events. Relatively few traders are consistently in the market for a majority of the days in the sample. Half of the sample are only in the market for 44 days (or 6 weeks out of a almost 2 year sample period). Individual trading events are short. 75% of trading events are 9 days or less with just 10% of events lasting approximately 1 month. The majority of trading events seem to occur within a short timeframe with half of traders waiting 1 week or less before re-entering the market. Just 5% of trading events occur after a 3 month gap between events.

Previous section had provided examples of the kinds of futures contracts retail traders are active in. We also observe that most retail traders invest in only one or two contracts. To that effect, Table IV shows the composition of account portfolios. The first column reports the number of different markets a trader is in across the account's lifetime

[6]Please note that after taking into account exchange holidays, we assume that any gap in the reporting of end-of-day positions greater than 3 calendar days to be a separate trading event.

while the second column looks at the number of markets an account holds during each individual trading event. Half of the accounts hold just a single market during each trading event. In just 10% of trading events we see accounts holding 3 or more positions simultaneously. While many traders stick to a single market between trading events, there is some evidence that at least a portion of traders switch between markets as they go in and out of futures market.

B. Trader Positions

While spread trades or rolling positions may be a relatively common strategy in larger portfolios, retail traders do not appear to trade multiple expirations of the same contract. Table V shows the distribution for the number of expirations held by traders in a single market and trading event combination. Statistics show that 99% of retail traders hold just a single expiration of a contract market per event (which means they do not hold any calendar spreads). Across an accounts life, we may see some traders holding multiple expirations of the same contract, but this is largely driven by accounts re-entering the market at a later point in time and holding a new front-month expiration as a result.

IV. Profit and Loss of Retail Traders

A. P&L Methodology

Next, we calculate profit and loss statistics for retail traders, aiming to understand how they come out in their futures trades. To explore the question of retail returns in futures markets, we calculate estimated P&Ls for each account and trading event. Our data provide us with end-of-day snapshots of each account's futures portfolio, which involves the number of contracts they hold in each expiration and their direction, as well as the date of that trading day. We do not observe their transaction prices or the time at which traders entered into or exited a particular position. As explained in further detail below, we use more of a marked-to-market approach.

To calculate P&Ls for futures trading accounts, we start by segmenting each account's trading history into discrete trading events. After taking into account exchange holidays, we assume that any gap in the reporting of end-of-day positions greater than 3 calendar days to be a separate trading event. Since we only observe end-of-day positions and do not know the time or the price at which traders transact positions, we use close-to-close averages of prices to estimate the transaction price. On each day we calculate the change in positions held between dates $t-1$ and t in each market for every account in the sample. If a trader had zero contracts on March 1st and 10 contracts on March 2nd, we would input this as a net increase of 10 contracts. We use the same approach when the positions were exited as well. Assume, for the same trader, we see end-of-day positions on March 7th, and no positions on the 8th. We know that trader got out of their position sometime on March 8th.

In order to calculate P&Ls, we need prices. Following with the same example, to value the net 10 contracts that trader started their futures trading with, we use the average of settlement prices on March 1st and the 2nd. Similarly, in order to find the price the trader got out of their positions at, we use the average of March 7th and March 8th settlement prices.

Table VI provides an example of a P&L calculation for a hypothetical trader in the CME Micro E-Mini contract. The trader first reported 10 contracts on April 6th. We know the trader entered into this position at some time between the close on April 5th and the close on April 6th. The notional P&L on the 6th is the 10 contracts multiplied by the average settlement price and the contract size of 5 units for a total notional portfolio change of -$203,200. The following day, the trader reduces their portfolio by 3 contracts. This transaction is priced at the average settlement price between April 6^{th} and 7^{th}. The trader did not change their holdings on the next day. Finally, on the 9^{th}, the trader reported 0 positions in the contract. We close out the account by assigning them a delta of -7 contracts at the average settlement price of the 8^{th} and the 9^{th} for a total cumulative P&L of $2,031.

B. P&L Results

Figure 3 shows the distribution of customer P&Ls during our sample. The distribution is fairly symmetrical with the median retail trader in futures markets having a small loss on the order of approximately a hundred dollars. There are long tails in both directions with a small number of traders realizing large gains or losses. However, visible inspection reveals that the left tail seems to have slightly fatter tails than the right tail.

In order to provide a more precise statistic, Table VII shows the the distribution of individual event P&Ls. The first column shows the median event P&L for traders who had multiple distinct trading events. In order to contrast, we show the P&Ls for traders who had just a single trading event separately in the second column. We note that both of the profit and loss extreme values seem to be higher, in absolute value, for single event traders when compared to multiple event traders. This is potentially due to larger profits, or losses, being associated with traders not wanting to return to the market. We also note that the 60% percentile of the P&L distribution corresponds to zero, or almost zero, profit for both groups. The fact that the P&L distribution is skewed left, both for single and multiple event traders, is in line with literature suggesting retail traders lose money on average (Jones et al. (2023); Ben-David and Hirshleifer (2012)).

C. Single vs. Repeat Traders

Having shown that the P&L distribution for single event traders seems to have higher kurtosis compared to multiple event traders, we further examine differences between the set of investors based on the number of times they enter the market. Table VIIIa divides traders into quintiles based upon the observed number of trading events for the account.[7] We also separately calculate their P&Ls from their first, last and other events. Specifically, $first\_p\&l$ is the actual notional P&L from the traders' first event in the market. $next\_p\&l$ is the average of P&L from all intermediate events. $last\_p\&l$ is the P&L of the final event we observe for the trader, before they disappear from our sample. In the first row, we see the set of traders with just a single trading event. Rows 2 to 5 report the quintiles of traders with multiple trading events. Surprisingly, traders who had just a single trading event, on average, had a worse initial notional P&L, than traders in any other group. In Table VIIIb, we present the same P&L numbers but they are now scaled by initial margin.

The difference in initial event P&Ls is statistically significant when we compare the group of single event traders against the aggregate set of multiple event traders. In a comparison of the P&L averages, we compare the last P&L of single event traders (mean of -897.35) against the set of first P&Ls from multiple event traders whose median first P&Ls are reported in the first column of rows 2 to 5 (mean -474.76).[8] This difference is significant with a t-stat of -5.71.

In the set of multiple event traders, we observe an increase in aggregate losses as the number of events increase. If in a given trading event, traders are expected to lose money, increasing the number of draws from this distribution leads to accumulated

[7] First quintile has single event traders, the rest of the traders get distributed into four even quartiles. This roughly translates into the following observation: 20% of traders have 1 trading event, the next 20% have 2-3 events, the next 20% have 4-10 events, and the last group have 10+ events.

[8] Averages are not tabulated, however medians are reported in table VIIIa.

losses over the account's lifetime. Furthermore, the last P&L we observe for traders is generally larger than the initial P&L or the P&Ls from the intermediate events. One interpretation is that traders are willing to re-enter the futures market as long as the losses are not too large, but once they have an event with more significant losses, traders are somewhat reluctant to invest again.

In order to remove any portfolio size effect that might be driving our results, in Panel B of Table VII we report the same P&Ls but with the notional values scaled by each traders initial margin. Results are qualitatively the same.

In Table IXa traders with multiple trading events are sorted based upon their first P&L (P&Ls are by scaled initial margin in Table IXb). In panel A, traders in the worst performing quintile when ranked on first P&L, continue to underperform in the intermediate events(t-stat of -12.22 when comparing average next P&L for traders in quintile 1 vs quintiles 2-5). Traders in the first quintile also have worse lifetime P&Ls when summing P&Ls over all trading events (t-stat of -32.93 for quintile 1 vs quintile 2-5). However, some of this continued under-performance can be explained by leverage, as traders in the lowest notional P&L quintile also have larger initial margins than other traders(T-stat of 28.263). In Panel B, when P&L is scaled by initial margins to remove this account size effect, while life-time P&Ls are still negative and significant(t-stat is -30.255) in part due to the initial under-performance, the intermediate P&Ls of other trader events are not significantly different between the traders with the worst initial under-performance and other traders(t-stat of -.77 for quintile 1 vs 2 to 5). However, when we consider traders who outperformed in the first event, both the notional and scaled P&Ls are significantly larger (t-stats of 2.98 and 2.06 respectively).

Overall, our findings show that retail traders in futures markets are comparable to retail traders in other markets. We show that some learning from trading takes place since our single-event traders tend to lose more in their first (and only) trading period, compared to multiple-event traders. This finding is supported with the learning by trading theories of Linnainmaa (2011) and Mahani and Bernhardt (2007), and is also in line with empirical observations from different markets (Barber et al. (2019), Seru, Shumway and Stoffman (2009)).

However, we also find that the number of events our multiple-event traders trade in does not change based on their initial P&L; those who lose big in the first event continue to trade in as many events as those who win big in their initial trial. These findings are supported by the learning to be overconfident idea of Gervais and Odean (2015), where traders take too much credit for their success as they try to infer their ability from their failures and successes.

We offer additional tests of traders learning by trading in the Appendix. Figure A1a presents P&L data on cohorts of traders in two separate ways. First figure groups traders by their futures trading entry month and tracks the group's P&L throughout events. Over time, due to attrition, the cohort loses traders, and the average P&L of the group increases with more events. This suggests that poorly performing traders who learn about their trading abilities drop out of the market, allowing average cohort P&L to rise. However, the figure shows that the remaining traders are still losing money, on average. Figure A1b groups traders by their maximum event number and presents average P&Ls by trader group. Figure shows that traders, on average, lose more money the longer they trade.

Finally, in Table A3 we regress P&L on event number separately per cohort and per trader. The per cohort regression tests whether the slope of the average P&L curve in figure A1a is positive or not, and we find that it is. With each additional event, the cohort is better off by about $5 in terms of their P&L. However, the large and negative intercept of the regression suggests the cohort keeps losing money on average even after many events. We find similar results in per trader regressions.

V. Entry and Exit Decision of Retail Traders

Having established that some traders choose to invest in futures only during a single event, while others invest through numerous events, we explore the entry and exit decisions by retail traders next. On each day of the sample, we count the number of accounts who entered or exited the futures market. We do this separately for each market and for traders who were long or short in the market. Using the daily count of entrances and exits, we estimate the following model for market m and day t:

$$\begin{aligned} Count\_Entrances_{m,t} = return_{m,t} + return_{m,t-1} + +return_{m,t-2} + return_{m,t-3} + \\ return_{m,t-4} + return_{m,t-5} + \gamma_m + year\_month_t \quad (1) \end{aligned}$$

where we hypothesize that entrances into, and exits from, the futures market will be associated with contemporaneous and past market returns. We also include market and month fixed effects in the model. We run our regressions separately for long and short entries and exits. For entries, it is possible traders might want to take directional position such as going long (short) when returns have been negative (positive). Similarly for exits, past positive or negative returns might have different impact on the decisions of long and short traders. Finally, we provide separate estimates for all event traders and for initial event traders in the tables below since initial entry decision might be different than re-entry into the market.[9]

[9] It is worth noting that our definition of initial entry is limited with our data sample. It is possible a retail trader might have traded futures before February 2021 and we might be misclassifying them. Given that average number of days retail traders spend investing in futures is 44 days in our sample, we think any potential misclassification would not introduce too much noise to our results.

A. Entrances

In Table X we present coefficient estimates for traders entering into long positions in futures markets. We hypothesize that entrance decision would depend on how the market returns have turned out in recent days. We also run separate regressions for entrance into the market for all events and compare them with first entrance into the market.

Results indicate that traders are contrarian, with entrances increasing after negative returns. This is especially true for all events cases, meaning traders' re-entrance decision depends on contemporaneous market returns. Focusing on first entrance decisions, we find that decisions are associated with lagged market returns, potentially hinting to the fact that it might take some time to open an account and trade futures for the first time.

Running the same sets of regressions for short entrants, we present our estimates in Table XI. Results are in line with the contrarian strategy we observe for the long entrants, however they are much stronger for contemporaneous returns compared than past returns, especially for the all events sample.

B. Exits

Next, we repeat a similar exercise for exits.[10] It is possible that the decision to exit the futures market might be driven by losses incurred contemporaneously, or after losses incurred for a number of consecutive days Barber et al. (2019). However, it is also possible that a trader might want to leave the futures market after enjoying gains, walking away with profits. Finally, we separately analyze the very last exit decision of the trader, the case when we no longer see that trader holding any futures positions.

Focusing on exits of traders who had long positions, Table XII shows that the number of traders exiting long positions increases with contemporaneous and lagged negative

[10]Exits, in our setup, indicate a break from holding any futures positions for at least a few days.

returns in the market. The fact that lagged returns in our regressions also have significant estimates suggests that accumulation in losses might be a factor in the exit decision of traders.

Next, we repeat the same exercise for exits of traders who had short positions. In Table XIII we identify similarly strong estimates when all events are included in the regression, suggesting the decision to exit the short position after positive contemporaneous and lagged returns. However, results are not quite as strong for last exits. It is likely that last exit decision for short traders might be driven by something other than market returns(e.g. hedging).

C. Initial Event

In the final set of tests, we explore the decision to return to futures markets and invest in a second trading event. We begin by using a sub-sample of our data that is just the set of the first trading events we observe along with a binary indicator variable, $Exit(0,1)$, set to 1 if the trader is a single event trader and did not return to futures markets during our sample period. Our explanatory variables are the scaled P&L from the first trading event i, along with the initial margin size(in thousands) and their interaction. Trade length in days is included as an additional control variable.

As suggested by Table VIIIa, single event traders had significantly larger losses in their first trading event than multi-event traders. What is less clear, however, is whether the decision to re-invest or permanently exit futures markets is driven by losses in notional terms or scaled percentage returns. To test this more formally, we estimate the likelihood of leaving futures markets based upon the traders P&L performance in the first trading event.

We estimate the following logit model:

$$Exit(0,1)_i = scaledp\&l_i + Margin_i + scaledp\&l_i * Margin_i + eventlength_i \quad (2)$$

Table XIV displays the results. As expected, *scaledp&l* is negative consistent with an interpretation that greater percentage gains (losses) is associated with an increased(reduced) likelihood of having a second trading event. On its own, $Margin$ is not significant, but when interacted with *scaledp&l* the coefficient is negative and significant. This suggests an amplification effect where traders with more capital invested with larger losses are even less likely to re-invest in futures markets. The joint hypothesis test of $H_0 : scaledp\&l + scaledp\&l * margin = 0$ is significant, $\chi^2 : 16.32$.

VI. Conclusion

We provide an analysis of the behavior of individual retail traders in futures markets using a regulatory data set on overnight positions and required margins. We carefully filter the data to end up with a representative sample of retail traders whose names do not carry any farm or corporation insignia, and whose maximum margin amount does not exceed $50,000.

We observe on average 7,000-8,000 retail traders per day in our 2021-2022 sample, with a high turnover rate. Traders do not stay in the market for too long (only about 4 days) and most hold one or two contracts. Retail investors tend to prefer micro contracts that have low notional amounts and correspondingly low margin requirements, and most traders have gains or losses of a few hundred dollars per trading event.

We track who takes a break and comes back to trade in the futures market, and who does not. We show that those single-event traders tend to have more extreme profits and losses in the tails, suggesting initial experience in the futures market can make a difference in their decision to come back or not. Overall, retail traders tend to act as contrarians when they enter the market, getting long (short) when the contract price declines (rises). They exit at higher than usual levels when the price moves against their position. We observe participants entering on the short side nearly as many times as on the long side; hence, there is little evidence supporting the conventional wisdom that retail is heavily biased toward holding long positions. Finally, we provide a formal test of what we observe regarding single-event traders in the data and find evidence that larger dollar losses on the first trade is significantly associated with leaving the market permanently.

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Figure 1: Average Required Margin, by Account

The figure presents the frequency of the average margin required, across the days in our sample, by individual trader account.

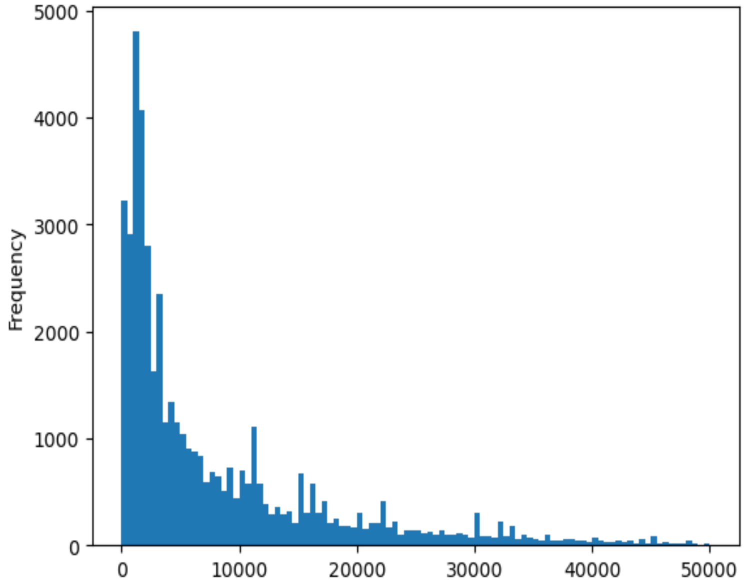


Figure 2: Number of Daily Accts

The number of daily accounts in our sample between February 2021 and November 2022.

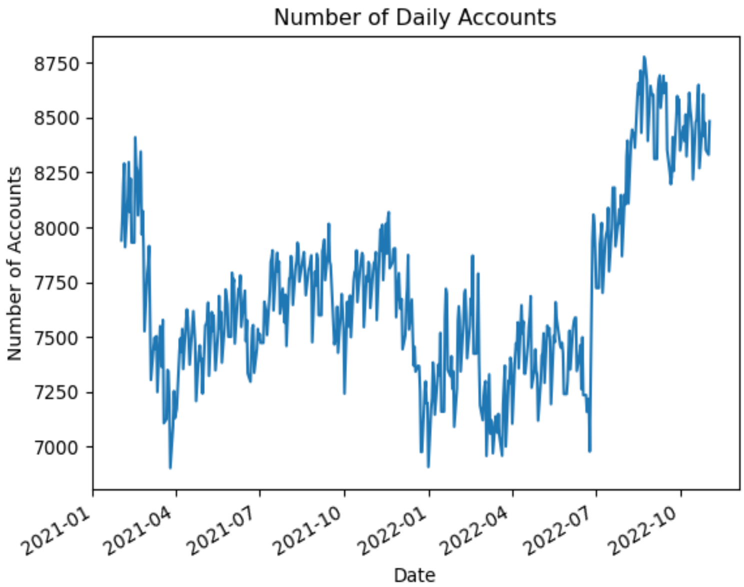


Figure 3: Net Profit and Loss Histogram

Aggregate Profit and Loss (P&L) across the lifetime of accounts, presented in 1,000s. The number of traders is on the Y-axis and trader P&L is in the X-axis, in thousands of dollars.

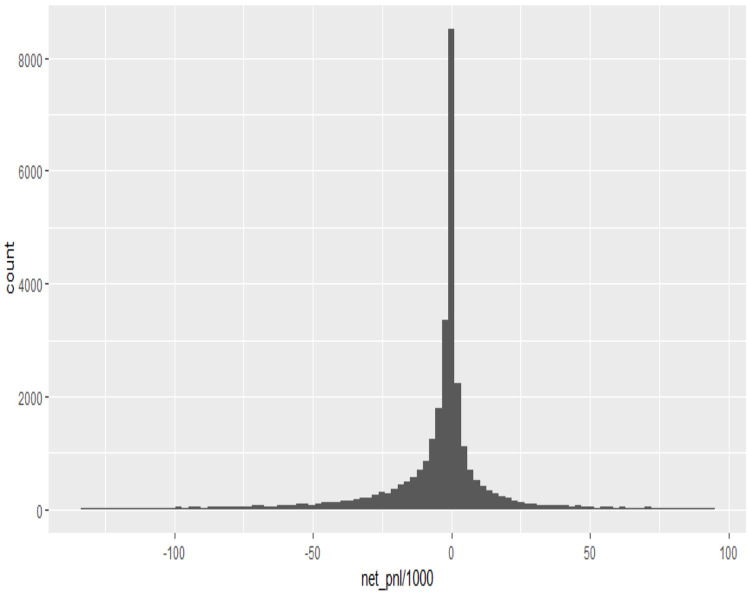


Table I: Margin Size

The table presents the margin held by traders. First column shows the corresponding percentiles. Second column presents margin size by trader, averaged across different events. Third column presents margin size by event. The fourth column is looking at changes in margin size between events.

Percentile	By trader	By event	Margin size change
0.01	30,394.60	32,000.0	91.83
0.05	19,122.31	19,400.0	72.83
0.10	14,914.92	15,000.0	59.09
0.25	8,960.00	8,200.0	31.25
0.50	3,840.00	3,240.0	0.00
0.75	1,702.08	1,500.0	37.50
0.90	1,100.00	1,000.3	125.00
0.95	865.55	750.0	233.00
0.99	365.00	296.0	706.14

Table II: Most Frequently Held Contracts (Daily Median)

The table shows the median number of accounts with positions in each market on a given day, averaged across our sample.

Commodity Name	Number of Accounts
MICRO E-MINI S&P 500 FUTURES	1704.5
MICRO E-MINI NASDAQ 100 FUTURES	1127.0
MICRO GOLD FUTURES	486.0
E-MINI S&P 500 FUTURES	452.5
MICRO E-MINI RUSSELL 2000 FUTURES	366.0
10Y TREASURY NOTE FUTURES	358.5
NYMEX CRUDE OIL FUTURES	279.5
MICRO E-MINI DOW JONES FUTURES	260.0
MICRO WTI CRUDE OIL FUTURES	203.0
NATURAL GAS HENRY HUB FUTURES	175.5

Table III: Account Trading Behavior

The table presents the summary statistics on number of events observed by retail trader and how often they are active in the market. First column shows the corresponding percentiles. Second column shows the number of trading events. Third column shows the number of days a traders holds position in the market. Fourth column shows the average number of days per event. Fifth column shows the average number of days between events.

percentile	num of events	num of days	days per event	days between events
0.01	1.0	2.0	2.0	4.0
0.05	1.0	2.0	2.0	4.0
0.10	1.0	4.0	2.0	4.0
0.25	2.0	11.0	2.0	5.0
0.50	4.0	44.0	4.0	7.0
0.75	10.0	141.0	9.0	17.0
0.90	20.0	275.0	27.0	45.0
0.95	28.0	361.0	50.0	85.0
0.99	45.0	463.0	133.0	236.0

Table IV: Composition of Trader Portfolios

Table shows the distribution of the number of markets retail traders invest in during their time in our sample. First column shows the corresponding percentiles. Second column shows the average number of markets invested by trader. Third column shows the number of markets invested in per event.

Percentile	market per trader	market per event
0.01	1.0	1.0
0.05	1.0	1.0
0.10	1.0	1.0
0.25	1.0	1.0
0.50	2.0	1.0
0.75	4.0	2.0
0.90	7.0	3.0
0.95	10.0	4.0
0.99	17.0	7.0

Table V: Number of Expirations Invested in

Table shows the descriptive statistics on the number of expirations invested in. First column shows the corresponding percentiles. Second column shows the average number of expirations per market. Third column shows the average number of expirations per market per event.

Percentile	expirations per market	expirations per market per event
0.01	1.0	1.0
0.05	1.0	1.0
0.10	1.0	1.0
0.25	1.0	1.0
0.50	1.0	1.0
0.75	1.0	1.0
0.90	2.0	1.0
0.95	2.0	1.0
0.99	3.0	1.0

Table VI: Profit and Loss Calculation Example

Table presents an example of a hypothetical profit and loss (P&L) calculation following our methodology.

Date	EOD Long Position	Delta Position	Settlement Price	Lag Price	Contract Size	Delta Notional	P&L
4/6/2021	10	10	4,064.00	4,067.70	5	203,200.00	-203,200.00
4/7/2021	7	-3	4,069.90	4,064.00	5	-61,048.50	-142,151.50
4/8/2021	7	0	4,089.00	4,069.90	5	0	-142,151.50
4/9/2021	0	-7	4,119.50	4,089.00	5	-144,182.50	2,031.00

Table VII: Distribution of Retail Profit and Loss

Table presents distribution of profit and loss (P&L) values for single event traders and for multiple event traders. First column shows the corresponding percentiles. Second column shows median event P&L for multiple event traders. Third column shows median event P&L for single event traders.

Percentile	Median Event P&L (multiple event traders)	Single Event Traders
10%	-2451.975	-6002.688
20%	-980.750	-2306.242
30%	-468.750	-1006.250
40%	-228.575	-448.000
50%	-95.000	-155.099
60%	0.000	12.000
70%	115.625	231.125
80%	350.000	819.740
90%	1093.950	2855.125

Table VIII: Profit and Loss - Ranked by Number of Trading Events

Table presents the average profit and loss (P&L) calculations incurred during the first investment day (first p&l), during the last investment day (last p&l), during intermediate investment days (next p&l), and aggregate investment event (agg p&l) by traders who traded in different number of event quintiles during our sample (event quintile). Panel A presents the dollar P&L calculations and Panel B scales those calculations by margin.

(a) Notional

event quintile	first p&l	next p&l	last p&l	agg p&l	num of events	margin
1	-	-	-154.000	-154.000	1.000	3000.000
2	-12.000	-143.000	-208.125	-529.375	2.387	3575.000
3	-38.750	-102.537	-178.250	-873.250	4.848	3823.250
4	-63.125	-161.925	-199.875	-1973.094	9.502	3820.019
5	-135.500	-222.921	-121.625	-5349.891	24.995	3980.722

(b) Scaled by Initial Margin

event quintile	first p&l	next p&l	last p&l	agg p&l	num of events	margin
1	-	-	-0.071	-0.070	1.000	3000.000
2	-0.008	-0.069	-0.096	-0.195	2.387	3575.000
3	-0.016	-0.037	-0.075	-0.311	4.848	3823.250
4	-0.030	-0.052	-0.096	-0.635	9.502	3820.019
5	-0.057	-0.071	-0.066	-1.690	24.995	3980.722

Table IX: Profit and Loss - Ordered by First Observation (multiple event traders)

Table presents the average profit and loss (P&L) calculations incurred during the first investment day (first p&l), during the last investment day (last p&l), during intermediate investment days (next p&l), and aggregate investment event (agg p&l) by multiple event traders, ordered by the their first investment day profit and loss calculation. (event quintile). Panel A presents the dollar P&L calculations and Panel B scales those calculations by margin.

(a) Notional

First P&L quintile	first p&l	next p&l	last p&l	agg p&l	num of events	margin
1	-4090.625	-717.347	-452.000	-12539.375	12.191	6594.590
2	-672.250	-234.021	-154.500	-2610.625	12.676	3262.361
3	-65.562	-97.125	-106.250	-762.500	11.825	2011.041
4	335.938	-72.192	-106.094	-173.438	11.501	2569.601
5	2726.938	-8.425	-186.000	2604.250	11.179	6077.778

(b) Scaled by Initial Margin

First P&L quintile	first p&l	next p&l	last p&l	agg p&l	num of events	margin
1	-0.756	-0.136	-0.139	-2.224	12.062	3724.920
2	-0.213	-0.081	-0.096	-0.852	12.631	3669.167
3	-0.031	-0.058	-0.058	-0.434	12.085	3837.500
4	0.129	-0.022	-0.062	-0.060	11.846	3676.136
5	0.608	0.009	-0.064	0.623	10.754	3621.364

Table X: Long Entrances

Table shows estimates from entrance regressions for long only traders. Dependent variable is equal to 1 when trader enters the futures market. *ret* is day-to-day market return and *lag_ret* is lagged returns. We run the regressions separately for traders' first entrances and for all of their entrances.

	Dependent variable:			
	All Events	All Events	First Entrance	First Entrance
ret	-73.526^{***}	-76.968^{***}	12.977	11.426
	(9.618)	(9.643)	(12.070)	(12.087)
lag_ret1		-2.718		-24.459^{*}
		(9.956)		(12.760)
lag_ret2		-21.097^{**}		-15.353
		(10.078)		(12.850)
lag_ret3		-52.528^{***}		-45.161^{***}
		(9.997)		(12.990)
lag_ret4		-2.748		-9.295
		(9.990)		(12.991)
lag_ret5		-10.348		0.701
		(9.981)		(13.088)
Market Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.576	0.577	0.087	0.089
DF	15,518	15,513	7,199	7,194
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table XI: Short Entrances

Table shows estimates from entrance regressions for short only traders. Dependent variable is equal to 1 when trader enters the futures market. *ret* is day-to-day market return and *lag_ret* is lagged returns. We run the regressions separately for traders' first entrances and for all of their entrances.

	Dependent variable:			
	All Events	All Events	First Entrance	First Entrance
ret	74.024^{***}	74.319^{***}	38.217^{***}	37.799^{***}
	(4.685)	(4.701)	(11.504)	(11.513)
lag_ret1		3.294		-28.126^{**}
		(4.941)		(12.243)
lag_ret2		4.521		1.240
		(4.942)		(12.257)
lag_ret3		3.981		-37.547^{***}
		(4.999)		(12.615)
lag_ret4		7.069		-12.617
		(4.973)		(12.557)
lag_ret5		0.487		1.299
		(4.973)		(13.095)
Market Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.722	0.722	0.073	0.075
DF	13,036	13,031	4,595	4,590
Note:				*p<0.1; **p<0.05; ***p<0.01

Table XII: Long Exits

Table shows estimates from exits regressions for long only traders. Dependent variable is equal to 1 when trader exits the futures market. *ret* is day-to-day market return and *lag_ret* is lagged returns. We run the regressions separately for traders' last exits and for all of their exits.

	Dependent variable:			
	All Events	All Events	Last Exit	Last Exit
ret	-91.093^{***}	-94.032^{***}	-67.528^{***}	-67.807^{***}
	(12.212)	(12.237)	(15.717)	(15.763)
lag_ret1		-65.334^{***}		-14.401
		(12.584)		(16.108)
lag_ret2		2.811		-1.470
		(12.521)		(16.091)
lag_ret3		-8.119		26.140
		(12.478)		(16.453)
lag_ret4		-21.594^{*}		-40.858^{**}
		(12.536)		(16.713)
lag_ret5		-56.078^{***}		-66.497^{***}
		(12.659)		(16.669)
Market Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.485	0.487	0.086	0.091
DF	15,075	15,070	6,832	6,827
Note:				*p<0.1; **p<0.05; ***p<0.01

Table XIII: Short Exits

Table shows estimates from exits regressions for short only traders. Dependent variable is equal to 1 when trader exits the futures market. *ret* is day-to-day market return and *lag_ret* is lagged returns. We run the regressions separately for traders' last exits and for all of their exits.

	Dependent variable:			
	All Events	All Events	Last Exit	Last Exit
ret	25.402***	26.075***	−12.411	−13.987
	(5.758)	(5.774)	(10.541)	(10.563)
lag_ret1		−3.223		5.195
		(5.921)		(10.958)
lag_ret2		16.314***		7.634
		(5.966)		(10.950)
lag_ret3		18.141***		14.939
		(5.971)		(10.946)
lag_ret4		5.812		−16.701
		(5.991)		(11.248)
lag_ret5		−9.263		−43.109***
		(5.999)		(11.558)
Market Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.663	0.664	0.104	0.107
DF	12,720	12,715	4,433	4,428
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table XIV: Logit Model: Likelihood of leaving after the first trade event

Table estimates the likelihood of permanent exit after first event. *scaledp&l* is profit and loss scaled by margin amount. *eventlength* is the number of days the event took. *margin* is total margin in 1,000 dollars. $scaledp\&l * margin$ is the interative term. The dependent variables is a 0/1 indicator where 1 means the individual left the futures market after the first observed trade event. The joint hypothesis test of $H_0 : scaledp\&l + scaledp\&l * margin = 0$ is significant. $\chi^2 : 16.32$

	Dependent variable:
scaled p&l	-0.001^{**}
	(0.001)
margin	0.002
	(0.001)
trade length	-0.0001
	(0.0003)
scaled p&l*margin	-0.010^{***}
	(0.003)
Constant	-1.188^{***}
	(0.017)
Note:	*p<0.1; **p<0.05; ***p<0.01

A. Appendix

B. Additional Results

A. Contract Sizes and Margin

Table A1: Contract Sizes and Margin
The table below shows the average initial margin and number of contracts held by retail traders in different futures markets.

Contract sizes differ and they also require different amounts of margin.

	Initial Margin	Long	Short
Commodity Name			
E-MINI NASDAQ 100 FUTURES	17,403.0	1.0	1.0
E-MINI S&P 500 FUTURES	15,537.0	1.0	1.0
COMEX 100 GOLD FUTURES	14,338.0	1.0	1.0
MICRO WTI CRUDE OIL FUTURES	7,466.0	3.0	3.0
MICRO E-MINI NASDAQ 100 FUTURE	6,732.0	3.0	3.0
MICRO GOLD FUTURES	6,438.0	3.0	3.0
MICRO E-MINI S&P 500 FUTURES	5,866.0	4.0	4.0
SB-SUGAR 11 FUTURES	5,367.0	3.0	4.0

Table A2: Predicted Probabilities for estimated logit model
Below I show the 95% confidence interval range for different predicted probabilities from the above logit model. The results indicate that their is a size effect in determining whether an individual returns to the market. The likelihood of a small portfolio(e.g. $1,000) returning is unaffected by the P&L of the first event, while the likelihood of larger portfolios (e.g. $11,000) returning is affected by P&L. There is a significant difference in the probabilities of the larger portfolio returning conditional on first event P&L.

FOTotalMarginAmount	margin_scaled_p&l	upper	lower
1.15	-0.417	0.241	0.229
1.15	-0.041	0.240	0.228
1.15	0.272	0.239	0.228
3.20	-0.417	0.243	0.232
3.20	-0.041	0.240	0.229
3.20	0.272	0.238	0.227
11.00	-0.417	0.252	0.238
11.00	-0.041	0.243	0.232
11.00	0.272	0.238	0.225

B. Learning by Trading Tests

Table A3: Retail Learning Tests

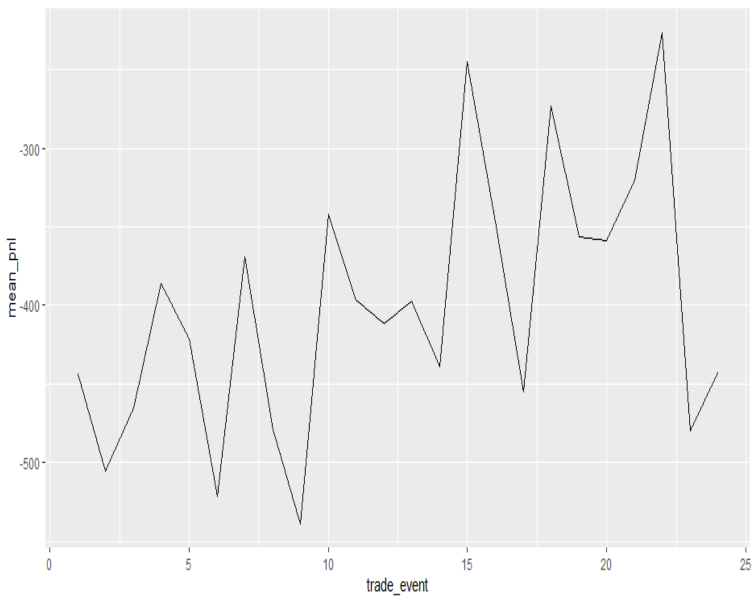
The below table reports the results of a regression of P&L onto the trade event number. Column 1 reports cohort level trade event P&Ls. Column 2 is trader level event P&Ls. Column 3 is trader level event P&Ls with cohort fixed effects included. White standard errors are used.

	Dependent variable:		
	Cohort Level	Tdr Level	Tdr Level
Trade Event	5.695^{*}	3.512^{***}	2.968^{**}
	(3.392)	(1.162)	(1.215)
Number of Traders	-0.029^{***}		
	(0.011)		
Initial Margin		0.066^{***}	0.067^{***}
		(0.002)	(0.002)
Constant	-442.154^{***}	-134.827^{***}	
	(39.817)	(13.097)	
Cohort Effect	No	No	Yes
Obs	446	193,744	186,154
R^2	.007	.0159	.0173
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure A1: Retail P&Ls by Trade Event

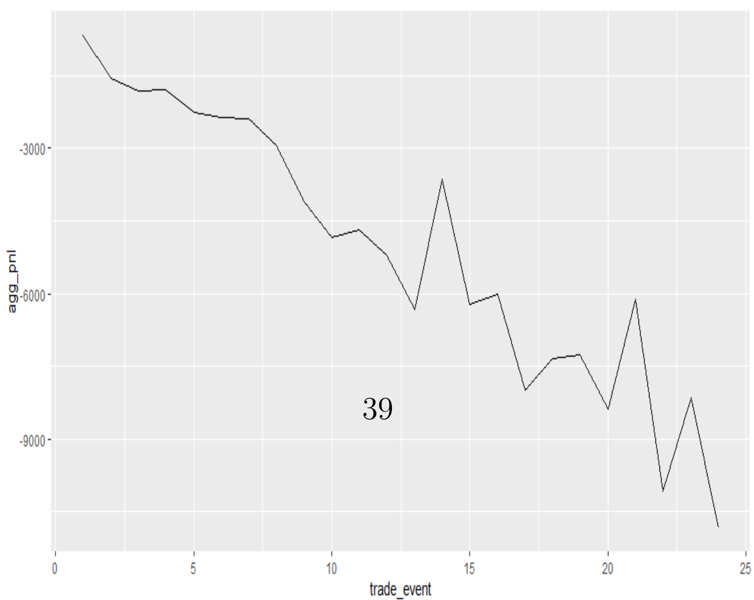
(a) Mean P&L by Number of Trade Events

The figure presents the mean event P&L of traders at each number of maximum events. Traders are grouped into cohorts based on the month the account first appears in the data. After each trading event, mean P&Ls are calculated by cohort and depicted in the table below.



(b) Aggregate P&L by Number of Trade Events

The figure presents the mean aggregate P&L of traders at each number of maximum events. Traders are grouped into cohorts based on the month the account first appears in the data. After each trading event, aggregate P&Ls are calculated by cohort for traders who exit the markets and have no further appearances in the data. Aggregate P&Ls for each trading event group are averaged across monthly cohorts.



C. Retail Traders as Percentage of Open Interest

Figure A2: Micro E-mini S&P 500: Aug 2022

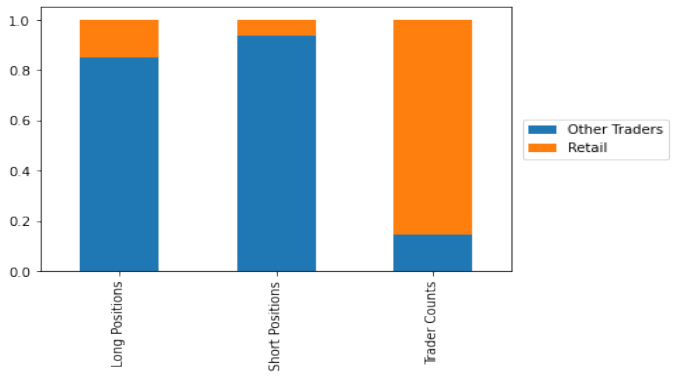


Figure A3: Corn: Aug 2022

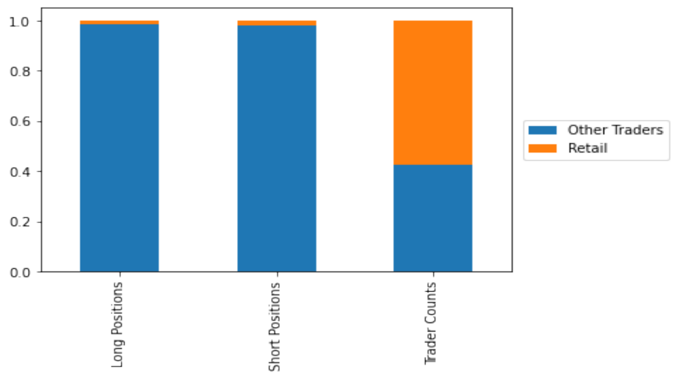


Figure A4: COT Comparison - E-mini S&P 500

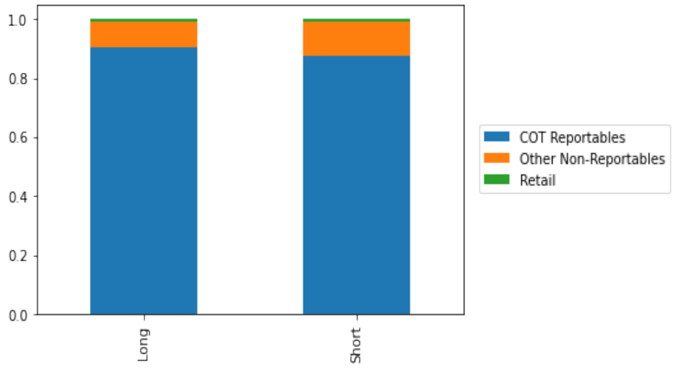
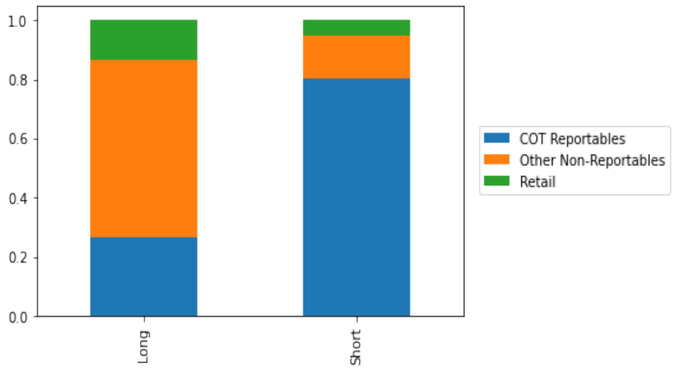


Figure A5: COT Comparison - Micro E-mini S&P 500



D. Exclusionary Words

In order to solely focus on retail traders, we remove traders with any one of the following words or suffixes in their name field from our sample.

['FARM', 'CATTLE', 'ETHANOL', 'DAIRY', 'RANCH', 'FEEDLOT', 'FEED', 'GRAIN', 'SWINE', 'PORK', 'AGRI', 'AGRO', 'COOP', 'CO-OP', 'LIVESTOCK','ELEVATOR', 'ELEV', 'SILAGE']

['CAPITAL', 'FUND', 'FUNDS' 'INVESTMENT', 'INVESTMENTS','MASTER', 'STRATEGY', 'TRADING', 'SECURITIES', 'SERIES', 'FUTURES', 'BANK','RETIREMENT', 'EMPLOYEE', 'EMPLOYEES', 'CORP', 'OPPORTUNITIES', 'AGENCY', 'PENSION','OMNIBUS', 'SEGREGATED',]

['llc', 'inc.', 'corporation', 'incorporated', 'company', 'limited', 'corp.', 'inc.', 'inc', 'llp', 'l.l.p.', 'pllc', 'and company', '& company', 'inc', 'inc.', 'corp.', 'corp', 'ltd.', 'ltd', '& co.', '& co', 'co.','co', 'lp']