Do Volatile Ostriches Run Faster?

TERM PAPER FOR SDS 88702

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Introduction

Myopic loss aversion (Benartzi & Thaler 1995) refers to the aversion experienced by most people when presented with a short-term view of potential losses. Building on prior theoretical work arguing for the central role that emotion plays in decision making under risk, Shiv et al. (2005) use the context of investment decisions to demonstrate a clear emotional basis of myopic loss aversion. Lo & Repin (2006) record significant real-time changes in professional traders' electrodermal and cardiovascular activity in the face of volatility. These findings upend traditional views of cold rationality in financial activity.

As an "interrupt system", emotion is a response to real-time needs that disrupt motivational goal hierarchies (Simon 1967). The motivation in investing is a very simple one – to make profits. Losses, or any event that draws on a cognitive association with loss, is in stark contrast to the overarching goal of investing. Such a strong signal to the interrupt system is likely to produce an immediate emotional response, that in an investment setting might manifest itself in behavior divergent from how a rational investor would (or should) ordinarily be expected to act.

Prospect theory dictates that losses loom larger over gains; it should follow that the prospect of losing will trigger a strong interrupt system (fear), which can have the effect of "crowding out" cognition. This is an unpleasant feeling; efforts to reduce it involves the seeking of information that contradicts such a position, and when that is not easily available, the avoidance of aversion-reinforcing information – dubbed "ostricity" (Karlsson et al. 2009; Loewenstein et al. 2014). One can draw similar arguments to explain intentional medical non-adherence as a form of ostricity; reminders to take the dose, and the dose themselves, are bitter pills to swallow when one feels averse to the idea of being diseased.

In an experiment where participants were prompted to "think like a trader", Sokol-Hessner et al. (2009) suggest this perspective shift resulted in a reduction of loss aversion and physiological arousal. While they don't detail participants' psyches, one can conjecture that the control group is more anxious owing to their belief of not being particularly skilled. When this belief is endogenously subverted in the treatment group, they exhibit less anxious behavior. Apparently, it is not the inherent uncertainty of the market, but one's belief about one's capacity to deal with this uncertainty, that determines the extent of one's fear of this uncertainty.

"A lot of pleasure and pain arises not from what we believe, but what we think about –what we pay attention to" -(Loewenstein, c. 2019). To explore the effect of exogenous determinants, in my study I focus on the rate of consumption of uncertainty-information. Specifically, I distinguish between real-time and in-hindsight attention, and how that plays out in trading. Loewenstein et al. (2014) observe selective attention in the face of a) bad news (down-markets), and b) uncertainty (volatility). I narrow my study's focus to uncertainty; I control for valence of news by having participants make a decision in both down- and up-markets. Individual psychological factors are bound to influence the choice to attend selectively. To control for these factors, I enforce inattention in one group by temporarily blocking all market information to them.

My hypothesis is that traders who were subject to real-time information are prone to be more cautious in their investment decisions, than their counterparts who view the same information in hindsight. This information break is a simulation of an investor pausing their trading activity by leaving their desk. A visit to the watercooler usually involves a distraction of some sort – gossip with colleagues, checking one's phone, or simply a moment of quietude. I predict that investors returning from the watercooler are better prepared to allocate their attention over a wider range of signals, than those actively (and narrowly) tracking the fluctuations at their desk (which I dub the *watercooler effect*). As a result, they are likely to be less susceptible to the hedonic impacts of price information, and I expect this to influence their trading decision. Both sets of traders make their trading decisions at the same points to facilitate an attribution to any divergence in behavior to their method of information consumption.

METHODOLOGY

I construct the market to have a single stock of a "big tech company". For the price movements, I used minute-by-minute prices of AAPL on NASDAQ between 18th September and 20th September 2019. This choice was made for the natural trend displayed by the stock – a steep rise and drop followed by a period of volatility which then smoothens out close to the mean. The price fluctuates only across a few cents over this period; such trivial price changes are unlikely to generate strong investor sentiment in a lab setting. Since the anticipatory "rush" of trading is key to my experimental context, I amplify the price changes by increasing the standard deviation of the trend.

79 Amazon MTurk workers participated in the study. The experiment consists of a 15-minute trading session. Before the experiment starts, participants are surveyed on their frequency of trading, and if they have investments they actively manage. Participant effort is sought by incentivizing every 100th winner with a monetary reward based on their earnings. They are acquainted with the interface, and provided detailed instructions on each stage of the experiment. Before the experiment begins, they are endowed with 10 shares ("T0"). They are informed that they will have two opportunities to make the trade, and must use the interim to observe price movements.

During Period 1 that lasts for 5 minutes, participants observe the price movement and its effect on their unrealized P&L of the initially-endowed stock. At the end of this period, they are allowed to make their first trade ("T1"). The experiment resumes, and the market enters into Period 2 characterized by a volatility in price movements. Half of the participants (referred to as "LiveTrackers" for the rest of this paper) are exposed to these wild swings; for the other half, the price graph freezes and they are encouraged to take a water break ("Hindsighter" group). Both groups are not allowed to place any trades during this period.

The experiment is constructed so that Period 2 ends with the stock in an up-market for half of the participants, and a downturn for the other half. At the end of Period 2, the LiveTrackers would have followed the volatile movements in real-time, but the Hindsighters only see what transpired while they were "away from their desk". Participants are then asked to make their final trade ("T2"). The price graph continues to update for another minute or so. The final screen surveys the participants about their attentiveness and affect during the experiment. Traded quantities and survey answers are recorded in a database for analysis. No personal information is collected during this process.

RESULTS & DISCUSSION

For a quantitative surrogate of investor confidence, I measure the fraction of available resources that is traded, as the ***quantum of trade (q).*** For example, if an investor has cash available to purchase 10 shares but they purchase only 6, the fraction of cash traded (***q)*** is 6/10 = 0.6. Similarly, if they have 5 stocks and sell 3 of them, the ***q*** of the trade is again 3/5 = 0.6. Values closer to 0 indicate a more conservative outlook, and a propensity for inactivity. A ***q*** of 1 is akin to going all-in on a poker hand you maximally believe to win, except that individual investors are price-takers and going all-in has no impact on the ***q*** of the others. In a field setting, ***q*** for buy-trades may be measured over the average investment amount favored by that investor. Measuring ***q*** for sell-trades is more straightforward, with the denominator simply being the number of shares held by the investor prior to making the sale.

REGRESSING q_{T2}

I fit an OLS Regression model to explain an investors' $\boldsymbol{q_{T2}}$ based on their $\boldsymbol{q_{T1}}$, cash available immediately prior to T2, number of stocks held prior to T2, the unrealized gains/loss on stocks held, and if the first trade was a purchase or sale. This model has an R^2 score of 0.31. In a second specification, I include a binary flag for LiveTrackers/Hindsighters, which raises the R^2 score to 0.348, indicating that a break in attention correlates with the subsequent ***q.***

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0033	0.001	-4.760	0.000	-0.005	-0.002
PNL_T2	-0.0022	0.002	-1.414	0.162	-0.005	0.001
q1	0.2119	0.195	1.088	0.280	-0.176	0.600
PurchaseFlag_T1	0.7960	0.179	4.459	0.000	0.440	1.152
AvblCash_T2	0.0002	5.13e-05	4.309	0.000	0.000	0.000
StocksHeld_T2	-0.0702	0.015	-4.760	0.000	-0.100	-0.041

Table 1. Regressing q_{T2} without LiveTrack flag

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0035	0.001	-5.114	0.000	-0.005	-0.002
PNL_T2	-0.0022	0.002	-1.417	0.161	-0.005	0.001
q1	0.2204	0.191	1.156	0.252	-0.160	0.601
PurchaseFlag_T1	0.7448	0.177	4.217	0.000	0.393	1.097
AvblCash_T2	0.0002	5.3e-05	3.527	0.001	8.12e-05	0.000
StocksHeld_T2	-0.0747	0.015	-5.114	0.000	-0.104	-0.046
LiveTrackFlag	0.2853	0.140	2.032	0.046	0.005	0.565

Table 2. Regressing q_{T2} with LiveTrack flag

In the following sections, I compare how both groups of investors behave when a) facing profits after volatility, and b) facing losses after volatility. Within each section, I summarize aggregate investor behavior as recorded in the experiment in a table, plot the distributions of ***q*** across both groups, and discuss its implications to the hypothesis being tested. It should be noted that owing to the small sample sizes, none of the distribution tests provided statistical significance.

Profit at T2

	LiveTrackers	Hindsighters
T1		
Active traders	**15**	**22**
Buyers	12	12
Sellers	3	10
Trade Volume	**116**	**161**
Buy	93 (81%)	96 (60%)
Sell	23 (19%)	65 (40%)
Mean q	**0.72 (0.35)**	**0.69 (0.36)**
Buy-side	0.7 (0.36)	0.73 (0.34)
Sell-side	0.77 (0.4)	0.65 (0.4)
T2		
Active traders	**18**	**21**
Buyers	5	6
Sellers	13	15
Traded Volume	**177**	**213**
Buy	62 (35%)	54 (25%)
Sell	115 (65%)	159 (75%)
Mean q	**0.68 (0.40)**	**0.73 (0.31)**
Buy-side	0.92 (0.38)	0.66 (0.23)
Sell-side	0.58 (0.41)	0.75 (0.34)
(q_{T2} - q_{T1}) %	**-5.00%**	**5.80%**
Buy-side	31.00%	-9.50%
Sell-side	-24.60%	13.33%
Participants	**20**	**24**

Table 1

At T1, we'd expect behavior across both groups to resemble each other as the experiment is identical for both so far. For some reason, the Hindsighters have a disproportionately larger number of sellers than all other groups at T1. The ***q*** exhibited by both groups are however similar enough for us to continue this analysis.

At T2, the market has gone through a volatile period and the stock is at a price higher than at T1 and T0, guaranteeing that every trader is facing unrealized gains. The number of buyers and sellers is equitable across both groups. Frenzied buying is observed amongst the LiveTrackers.

The bulk of trades at T2 are on the sell-side, as seen in Table 1. This is in line with the disposition effect – traders are more likely to sell a winning stock to realize gains. The Hindsighters appear to be quicker to sell, with 9 out of 15 sellers disposing off their entire stock. In comparison, the LiveTrackers exhibit a more moderate ***q***.

Figure 1 depicts how ***q*** is distributed for both groups at both points in time. At T1, both groups appear to trade bimodally. At T2, there appears to be a general shift towards ***q=1***. Figure 2 plots the buy-side and sell-side ***q*** for both groups at T2.

The changes in ***q*** on the buy-side contradicts my hypothesis, but on the sell-side it aligns with what it guesses.

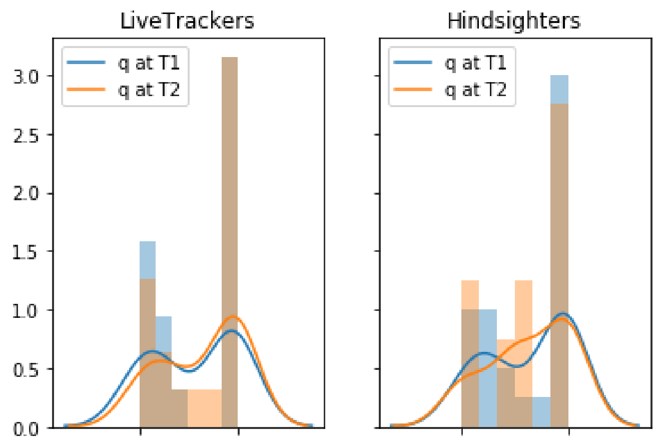

Figure 1. Distribution of q when facing gains at T2

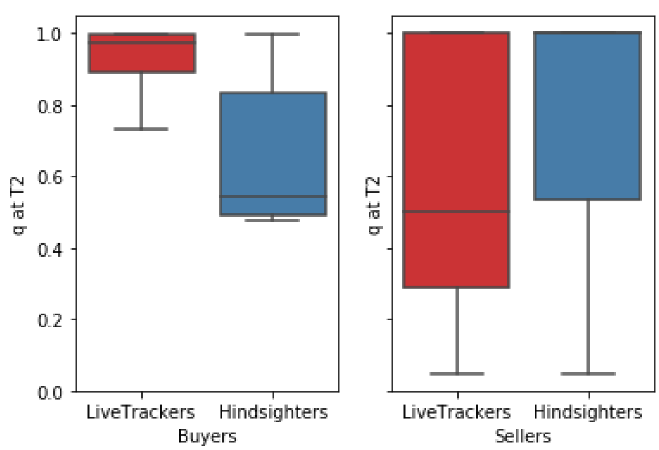

Figure 2. Boxplot of q at T2, when facing gains at T2

Loss at T2

	LiveTrackers	Hindsighters
T1		
Active traders	**17**	**14**
Buyers	14	10
Sellers	3	4
Trade Volume	**120**	**103**
Buy	100 (83%)	86 (83.5%)
Sell	20 (17%)	17 (16.5%)
Mean *q*	**0.65 (0.31)**	**0.68 (0.32)**
Buy-side	0.65 (0.28)	0.71 (0.31)
Sell-side	0.67 (0.49)	0.57 (0.4)
T2		
Active traders	**18**	**17**
Buyers	11	5
Sellers	7	12
Traded Volume	**126**	**167**
Buy	59 (47%)	44 (26.4%)
Sell	67 (53%)	123 (73.6%)
Mean *q*	**0.63 (0.29)**	**0.72 (0.29)**
Buy-side	0.67 (0.23)	0.77 (0.23)
Sell-side	0.55 (0.38)	0.70 (0.33)
(q_{T2} - q_{T1}) %	**-3.00%**	**5.80%**
Buy-side	3.00%	8.45%
Sell-side	-18.00%	18.57%
Participants	**18**	**17**

Table 2

While facing losses, the behavior of the Hindsighters is more in line with what I expect. LiveTrackers facing losses display a strong disposition effect, with more buyers than sellers. The ***q*** for buyers in LiveTrackers has increased at T2; this behavior may be due to a belief in mean-reversion, adjudging T2 to be a good buy-low position for a potential sell-high. The increase in ***q*** on the buy-side for both groups might follow from a sense of this purchase being a good deal.

The volume of sellers among the Hindsighters indicates an apparent contradiction of the disposition effect. While this could be characteristic of this particular cohort of 17 participants, it would be interesting to see if such behavior replicates across a larger group. Assuming that it does, this contradiction maybe due to a lower salience of the unrealized loss they face.

In Figure 3, it seems that the Hindsighter group exhibits a higher ***q*** in their T2 compared to their T1, and an increased propensity to go all-in compared to the LiveTrackers.

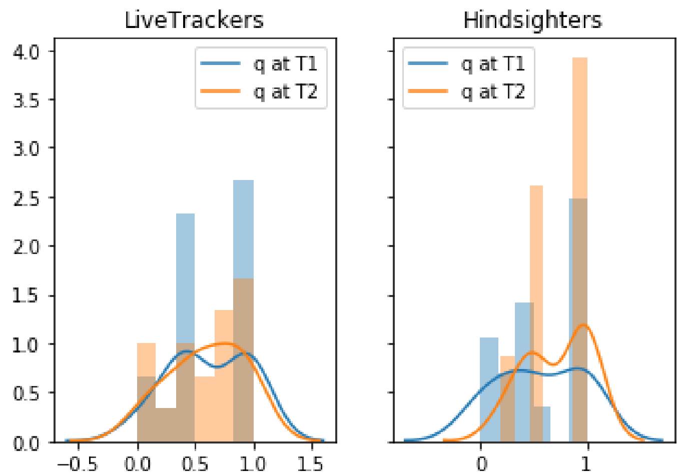

Figure 3. Distribution of q when facing losses at T2

There is an interesting inversion of behavior between the LiveTrackers and Hindsighters. Selling made up 73% of all Hindsighter trades at T2 (versus 53% for LiveTrackers), in a seeming contradiction of the disposition effect. Buying stock can be thought of as risk-loving behavior due to the uncertainty associated with future prices of the asset. The act of selling, or exiting an uncertain position for a known fixed price, can be analogously viewed as risk-aversion. The Reflection Effect posits risk-aversive behavior in gains and risk-loving behavior in loss. Such behavior is modally exhibited by all groups of investors except the Hindsighter-Loss, where a majority of the investors display risk-averse behavior (or selling) in the face of unrealized loss.

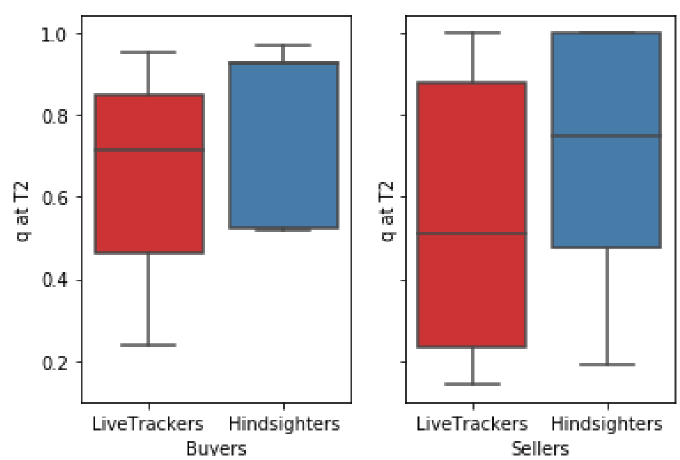

Figure 4. Boxplot of q at T2, when facing losses at T2

Attention drives trading activity; this study explores how a break in attention during volatility impacts trading decisions. The watercooler effect predicts such a break dampens the hedonic impact of fluctuating prices. Indeed, participants in the Hindsighter treatment were modally calm, as opposed to a modal feeling of optimism amongst the LiveTrackers (Appendix A1.4). The watercooler effect also appears to influence the risk-appetite of investors; they trade a higher fraction of resources than the LiveTrackers. This inversion in behavior is most distinct when facing unrealized losses; the Hindsighter group's behavior is inconsistent with the disposition effect seen in the LiveTrackers. While the results are not statistically significant, a graphical comparison of the behaviors show a difference.

LIMITATIONS

The experiment does replicate the complexities of a large stock market. The objective of this study is to explore if investment tendencies differ based on the rate of information consumption, as observed in a simple laboratory experiment. My intention was to use these findings to inform a future larger-scale study that honestly replicates the experience of online trading systems favored by most individual investors. As such, the current study retains only the very basic elements of trading: the market consists of a single stock, participants can place trades only at pre-specified moments, a very limited number of trades (2) is permitted.

In the next such study, I would make the following changes to the experimental setup:

a) Allow participants to make trades freely, and not at pre-specified points in time
b) Have multiple stocks on the market
c) Instead of blocking out the price signals to the Hindsighter group, have them attend to a task that is moderately cognitive
d) Have a longer trading session

CONCLUSION

Tracking volatile price shifts in real-time leads to expectations and immediate feedback. Akin to Prospect Theory, a belief that is confirmed feels nice, but a contradiction is more of a setback. A string of these is likely to create an emotional turbulence. Moreover, they are likely to act on the representative heuristic, which might lead to a fallacious belief in mean reversion. The tunnel vision of livetracking maximizes attention on and salience of the price movements, crowding out the processing of other information, exo- and endo-genous, that may be pertinent to making rational decisions that are not overly influenced by immediate affect. More robust experimental design and a larger participant cohort may uncover mechanisms where the rate of information consumption informs subsequent emotion and behavior.

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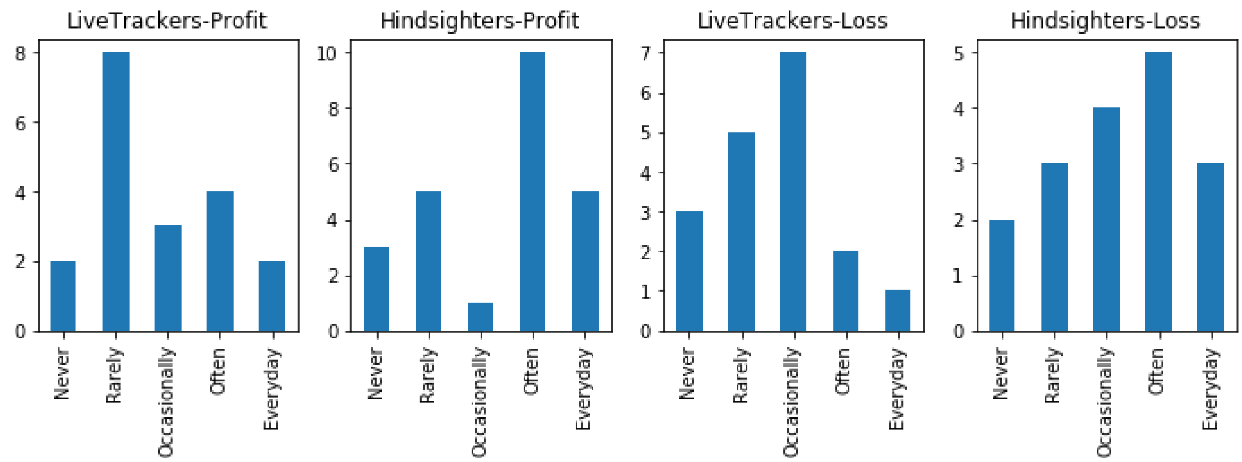
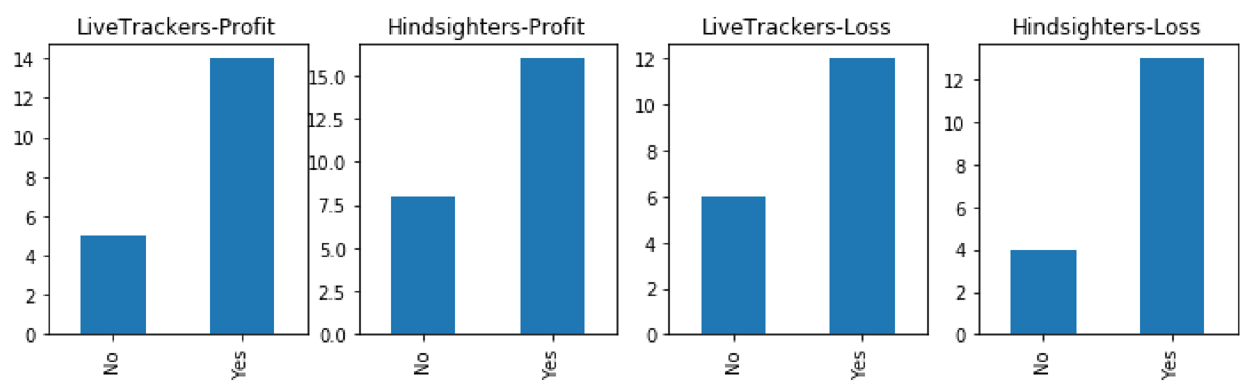
APPENDIX

A1. SURVEY ANSWERS

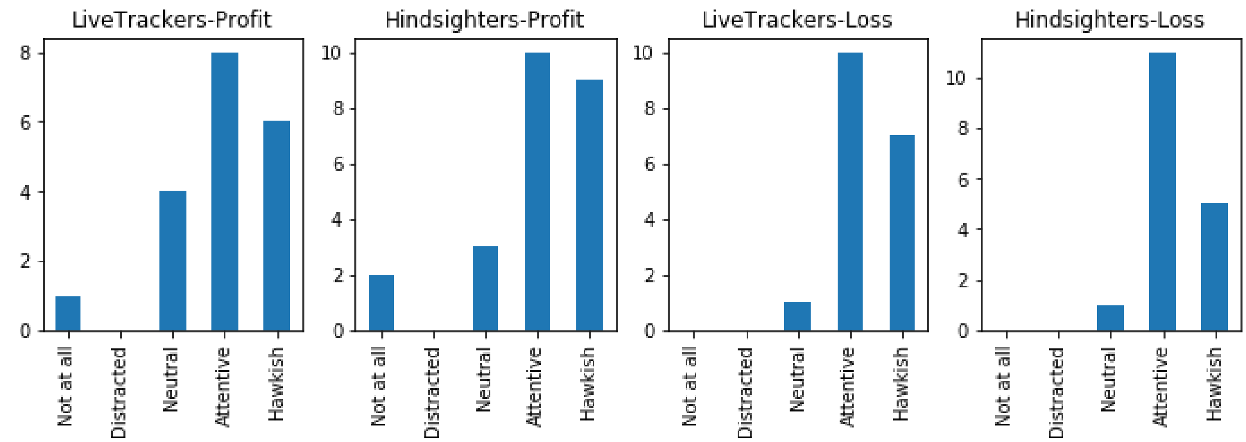
A1.1 How frequently do you trade on the stock market?



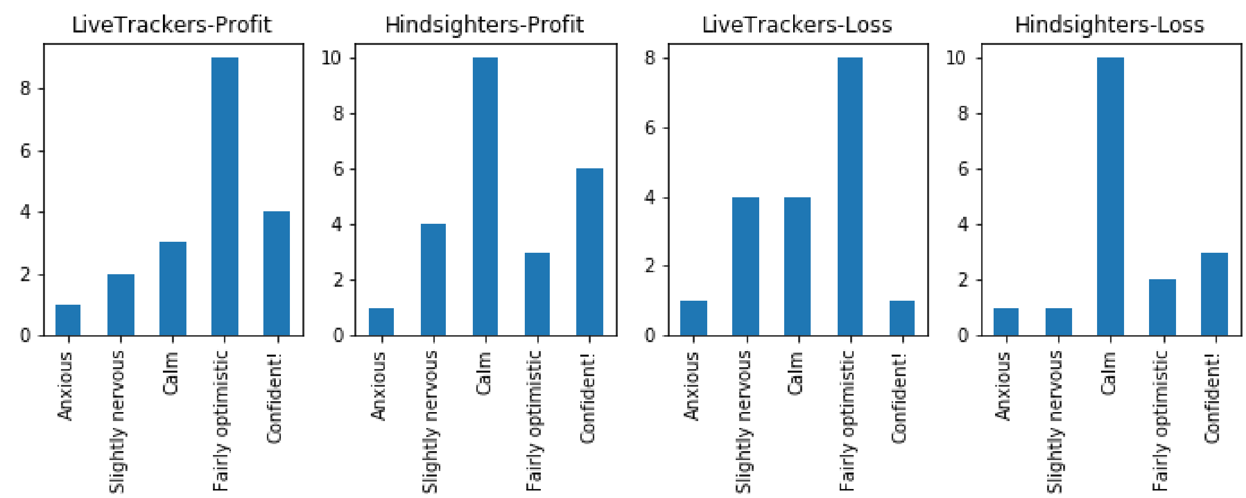
A1.2 Do you have any investments you actively manage?



A1.3 How focused were you on the stock movements?



A1.4 How did you feel between the first and second trade?



A1.5 Given an option, would you change your trades?