Counting pennies, losing pounds: Biased learning about own trading ability*

Fernando Chague† Bruno Giovannetti‡

Bernardo Guimaraes§ Bernardo Maciel¶

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Abstract

We study the behavior of retail day traders to shed light on the causes of overconfidence in financial markets. We show these individuals assess their trading skills using a simple counting heuristic: the proportion of profitable days. This yields an upward-biased performance measure, as individuals exhibit a strong disposition effect that artificially inflates the proportion of profitable days. We develop and estimate a model showing that without the disposition effect, the counterfactual proportion of profitable days would be 47%, compared to the actual 52%. Our findings show that the disposition effect, combined with simple heuristics for evaluating performance, can generate overconfidence.

JEL Codes: G11, G40, G41

Keywords: overconfidence, retail investors, counting heuristic, disposition effect

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†Sao Paulo School of Economics – FGV, Brazil. E-mail: fernando.chague@fgv.br.

‡Sao Paulo School of Economics – FGV, Brazil. E-mail: bruno.giovannetti@fgv.br.

§Sao Paulo School of Economics – FGV, Brazil. E-mail: bernardo.guimaraes@fgv.br.

¶University of California, Berkeley - Haas School of Business. E-mail: bernardo_maciel@berkeley.edu.

1 Introduction

Counting the number of successes is a helpful heuristic to infer skill levels across various fields. It is often a cost-effective way of getting a good performance assessment. We show that individuals trading in the stock market also evaluate their performance by counting the number of wins, but this produces an upward-biased performance measure. Our findings reveal a key driver of the well-documented overconfidence among individuals actively trading in the stock market.

Our dataset includes all trading activity of all Brazilian retail day traders from 2012 to 2018. Day trading[1] is particularly useful for studying the role of counting heuristics in inferring trading skills for two reasons. First, the vast majority of individuals lose money day trading – 97% of all individuals in this dataset who day-traded for more than 300 days lost money after trading costs were considered (Chague, De-Losso, and Giovannetti, 2019). Therefore, quitting day trading is an observable behavior of effective self-assessment and learning regarding own trading ability. Second, day trading yields a data point every trading day. Hence, we can accurately identify the date individuals quit (their last day of day trade).

We first show that decisions to continue or quit day trading are based on a simple counting heuristic, the proportion of profitable days. Controlling for this, actual financial results do not seem to matter. We then show that this heuristic induces individuals to be overconfident: owing to the disposition effect, average daily losses are substantially larger than average daily gains, implying that the simple number of successes is an upward-biased performance measure.

We focus our baseline analyses on 39,744 individuals who began to day-trade during our sample period, did so for at least 30 trading days, and eventually quit day-trading.

[1] A day trade consists of buying and selling the same amount of the same instrument (e.g., a stock or a futures contract) within a single trading day.

We study their quitting decisions.

We start by showing that the probability of an individual quitting day trading on a given day is a discontinuous function of the result obtained on that day, with a large jump at zero. Losing 100 dollars or 10 dollars predicts the same probability of quitting (about 7%, when we focus on each individual's last 20 trading days). In turn, winning 10 dollars or 100 dollars predicts a much lower probability of quitting (about 3%). That is, the quitting decision depends not on the amount the individual wins or loses on the day but simply on whether the result is positive or negative.

If winning or losing (any amount) is what predicts quitting, it seems individuals simply count wins to infer their skill. To confirm this, we run panel regressions, modeling the decision to quit day trading on a given day as a function of cumulative past performance. We control for individual-level fixed effects to take into account omitted variables at the individual level that can affect the quitting decision (such as income, overall trading skill, and IQ). We confirm that the proportion of profitable days, not the total financial result, explains quitting. An increase of 10 percentage points in the proportion of profitable days reduces the probability of quitting by 0.58 percentage points (a large effect given that the unconditional probability of quitting is 1.29%). We run a number of robustness exercises, such as focusing only on futures contract day-trading,[2] examining the number of days until the next day-trade as an alternative outcome variable to quitting, and exploring different ways of identifying the first and last day trades. Results remain consistent.

Accurately assessing the performance of financial portfolios is challenging, requiring the computation of a time series of portfolio returns and its regression on a set of well-chosen risk factors to obtain the portfolio alpha. In contrast, calculating a nearly

[2] In futures trading, all trades must be settled at the end of the day as settlement occurs daily in the futures market, unlike in equity trading where an individual might decide to roll the paper gain or loss to the next day.

perfect measure of day-trading performance is simple: one only needs to sum up daily day-trading financial results. Therefore, our finding that individuals assess their day-trading performance by counting wins is particularly surprising.

This simple counting heuristic would not be problematic if the proportion of profitable days were an unbiased measure of day-trading overall performance. We then show this is not the case.

The distribution of individuals' daily results is highly skewed to the left. Day traders do have more profitable days than losing days. However, average daily losses are larger than average daily gains, and their overall result is negative. Indeed, the 39,744 individuals profited on most days they traded (52.3%) but, at the same time, had a total gross loss in excess of 100 million dollars.[3] The proportion of profitable days gives individuals a false impression of good trading performance.

A possible explanation for the left-skewed distribution of daily profits is the well-known disposition effect (Shefrin and Statman, 1985, Odean, 1998, Weber and Camerer, 1998). This behavioral bias has been shown to affect individual investors in several countries, for some groups of professional investors, different types of assets (see the survey in Barber and Odean, 2013), and also for day traders (see Linnainmaa, 2003, Linnainmaa, 2005, Jordan and Diltz, 2003, and Heimer, 2016). Owing to the disposition effect, a day trader who starts the day winning will be inclined to close the position and call it a day but, when facing losses, will tend to persist in trading during that day, trying to recover. Doing so artificially increases the frequency of profitable days at the expense of larger daily financial losses when they occur.

We show that asymmetric day-trading results are related to the disposition effect by analyzing a subsample of day traders for whom we observe their entire intraday trading activity, deal by deal. For 3,980 individuals, representing a random sample of

[3]Considering trading costs, taxes, and expenses on trading courses, trading losses would be even larger.

10% of our population of day traders, we have a granular dataset with complete records of all their day-trading deals. There are 13,130,771 deals in this dataset.

Using these deal-by-deal data we show that: individuals display a strong disposition effect when day-trading; individuals with a stronger disposition effect also display a higher proportion of profitable days and more skewed daily results; the disposition effect increases over time as individuals continue day-trading, progressively inflating the proportion of profitable days; and individuals' actual trading skill does not increase over time.

Finally, we develop and estimate a model to infer the counterfactual proportion of profitable days among day traders if they displayed no disposition effect. In the model, a day is divided into two trading sessions. During session 1, an individual makes a bet. If the result is positive, they call it a day, but if it is negative, they place another bet. The size of the second bet is the absolute value of the loss of the first session times a parameter α. The parameter α captures the day traders' propensity for the disposition effect. The case $\alpha = 0$ implies no disposition effect and a symmetric distribution of gains. A larger α leads to higher odds of wins in a day and higher skewness.

We estimate the model parameters by GMM targeting the key moments describing traders' performance: the average, variance, and skewness of their results, as well as the proportion of winning days. Our estimates indicate that the proportion of profitable days in the absence of the disposition effect would be 46.7%, significantly below the observed number of 52.3%. Using our deal-by-deal dataset, we confirm that individuals' actual day-trading skill is indeed below 50%.

We also employ the model to understand whether α changes over time as an individual continues to day-trade. We restrict our sample to individuals who decided to day-trade for more than 250 days before quitting and estimate the model's parameters for different time intervals. We find that α increases as individuals continue to day-trade, so the distribution of daily results becomes even more left-skewed with time. Because of that, while the estimated actual skill is roughly constant at around 47% over time, the odds of positive profits on a given day rise with time (from 51.5% to 56.7%). As individuals persist in day trading, their behavior artificially inflates the simple counting heuristic. Perhaps surprisingly, the reluctance to accept losses on a single day actually grows with trading experience.

Our paper is closely related to Gödker, Odean, and Smeets (2023), although their research environment and methodology are very different from ours. First, they analyze a survey of retail investors from a Dutch financial institution and show that the disposition effect correlates with overconfidence among individuals. Then, using an online experiment, they find a causal effect of the disposition effect on overconfidence.

Our paper is also related to the findings of Ungeheuer and Weber (2021) and Ungeheuer and Weber (2023). Ungeheuer and Weber (2021) conduct four laboratory experiments to explore how correlations across stocks are perceived. They find that individuals base their decisions on a simple heuristic: counting the number of times stocks move in the same direction. Ungeheuer and Weber (2023) show that individuals also seem to rely on frequencies to determine which assets are likely to outperform. Through lab experiments, they find that stocks which more frequently outperform others are more likely to be selected by participants, even though these stocks are first-order stochastically dominated by assets that underperform frequently.

Our paper contributes to the broad literature on individuals' overconfidence, and more specifically, on how individuals learn about their trading skill — see Odean (1999), Gervais and Odean (2001), Bénabou and Tirole (2002), Köszegi (2006), Mahani and Bernhardt (2007), Grinblatt and Keloharju (2009), Deaves, Lüders, and Luo (2008), Seru, Shumway, and Stoffman (2010), Linnainmaa (2011), Eil and Rao (2011), Campbell, Ramadorai, and Ranish (2014), Zimmermann (2020), Gödker, Jiao, and Smeets

(2024). If retail investors are overconfident about their abilities due to errors in evaluating their trading performance, as we show, there is potential for welfare improvement. Regulators might need to worry about providing better information to individuals.

Our paper also relates to a recent literature on belief updating, specifically on why people make errors when updating beliefs based on noisy signals. Bordalo et al. (2023) argue that individuals might focus on certain salient features of a problem, neglecting non-salient but equally important ones. In our context, the salient feature that day traders consider is the winning frequency, which is an easy measure to recall. Ba, Bohren, and Imas (2023) model belief updating as a two-stage process where people first simplify the information structure of the problem they face, and then form beliefs that might be subject to errors. They find that noisier signals lead to overreaction. Augenblick, Lazarus, and Thaler (2024) find that while individuals might agree on the direction of the belief update, they tend to overreact to weak signals and underreact to strong ones. To the extent that the magnitude of day-trading results indicates the strength of the signal, our findings are consistent with day traders underreacting to strong signals and overreacting to weak signals, as both very negative results and close-to-zero results predict the same quitting likelihood.

Finally, our findings also contribute to a body of literature showing that retail investors typically incur losses from trading — see Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000), Barber and Odean (2001), Barber, Lee, Liu, and Odean (2008), Barber and Odean (2013), and Barber, Lin, and Odean (2023) — and, more specifically, to the literature about losses on day-trading — see Linnainmaa (2003, 2005), Jordan and Diltz (2003), Choe and Eom (2009), Ryu (2012), Kuo and Lin (2013), and Ben-David, Birru, and Prokopenya (2018). Barber et al. (2020) and Chague, De-Losso, and Giovannetti (2019) point out that persistent day traders have some of the worst performance, which is the opposite one would expect based on learning-by-doing or revealed expertise explanations. These findings have left researchers with the puzzle of why many retail day traders take so long to quit. Investors forgetting their losses (Ben-David, Birru, and Prokopenya 2018, and Gödker, Jiao, and Smeets 2024), or using upward-biased heuristic to compute their performance (as shown by us) could be complementary explanations.

The remainder of the paper is organized as follows. Section 2 presents our dataset. Section 3 shows that individuals' decisions to continue day-trading are explained by their proportion of profitable days. Section 4 shows that the proportion of profitable days is an upward-biased measure of day-trading performance, inflated by the disposition effect, and presents a model to estimate the actual skill of day traders from daily results. Section 5 concludes.

2 Data

The dataset come from CVM (Comissão de Valores Mobiliários), the Brazilian SEC, and spans 2012 to 2018. It is at the investor-day level and contains the day-trading gross profit (excluding all transaction costs) for all individuals who day-traded in Brazil.

We define a day trade as the trade activity during a day when the individual buys and sells the same amount of an asset (the gross profit is then the total revenues from sales minus the expenses from purchases). We compute the day-trading gross profit of each individual on each day as their aggregate gross profit across their day-trading activity in stocks (all stocks listed in the Brazilian stock exchange) and two future contracts very popular among individuals who day-trade: *mini-índice* (mini-index) and *mini-dólar* (mini-dollar).[4] For each pair individual-day, we observe an

[4]Day traders operating mini-index try to predict intraday variations in the stock market index (Ibovespa). In turn, day traders operating mini-dollar try to forecast intraday variations in the exchange rate between dollars and Brazilian reais. These future contracts allow individuals to day-trade using massive leverage, about 400 times the value deposited with the broker, a feature that

anonymous identification variable for the individual that remains constant over time, and we compute their total day-trading gross profit (across mini-index, mini-dollar, and stocks).

We use the first year of our dataset, 2012, to identify each individual's first day of day-trade. We say an individual began to day-trade on a given day if we see no day-trading activity from them before that day and discard anyone who day-traded in 2012 from the sample.

We observe 241,452 individuals beginning to day-trade from 2013 to 2018. Out of these, 50,536 individuals day-traded for more than 30 trading days — a minimum level of persistence to be considered in our baseline analysis. Moreover, since our primary goal is to study when and why individuals quit day-trading, in our baseline analysis, we exclude individuals who have day-traded in the last two months of our sample (November and December 2018) – for whom our sample may be censored. We end up with 39,744 individuals who began to day-trade between 2013 and 2018, day-traded for more than 30 days, and eventually quit day-trading.[5]

A first-pass analysis of the data shows an intriguing relation between how many days individuals day-traded before quitting, the proportion of days with a positive result, and their total profits. We divide the 39,744 individuals into 12 groups according to the number of active days until they quit. Group 1 contains individuals who day-traded from 31 to 50 days during 2013-2018; Group 2 comprises individuals who day-traded from 51 to 70 days, and so on, until Group 12, with individuals who day-traded for more than 250 days before quitting.

Table 1 presents the number of individuals in each group along with i) the proportion of individuals in the group with $TotResult > 0$ (positive total gross profit) and ii)

attracts day traders.

[5]For these 39,744 individuals, 80.4% of their day trades are in future contracts (mini-index and mini-dollar, where they can leverage) and 19.6% are in stocks.

the proportion of individuals in the group with $Prop > 50\%$ (proportion of days with positive gross profit greater than 50%).

[Table 1 about here]

The table shows that 48% of the 39,744 individuals presented positive gross results in more than 50% of the days, but, at the same time, only 20% of them had a total positive gross result. These seemingly contradictory facts come from the distribution of daily results being highly skewed to the left, as we will discuss ahead. The table also shows that, as a group, the 39,744 individuals profited on most days they traded (52.3%) but, at the same time, had a total gross result of -105.8 million dollars.[6]

Interestingly, Table 1 also shows that groups comprising individuals who traded more show, on average, a higher fraction of individuals with $Prop > 50\%$ (Column 5) but a lower fraction of individuals with a positive total result (Column 4). Do individuals look at the proportion of profitable days (and not at the total financial result) to infer their performance and decide to continue or quit day-trading? We answer this question in the next section.

3 Deciding to quit day-trading

It is well-known that individuals in general lose by day-trading — see Linnainmaa (2003, 2005), Jordan and Diltz (2003), Choe and Eom (2009), Ryu (2012), Kuo and Lin (2013), and Barber et al. (2020). According to (Chague, De-Losso, and Giovannetti, 2019), 97% of all individuals in our dataset who day-traded for more than 300 days lost money after trading costs were considered. Hence, there is a clear observable behavior

[6] The average loss per person is 2.7 thousand dollars, similar to the Brazilian quarterly income per capita.

that reflects individuals' effective learning about their own day-trading skill: quitting day-trading.

This section presents evidence that individuals' decisions to quit or continue day-trading are explained by an incomplete measure of their trading performance: the simple proportion of days with a positive result.

We first show that the probability of a day being an individual's last day-trading session is a discontinuous function of the result obtained on that day with a large jump at zero. We initially focus on the last 20 days of day-trading of the $39,744$ individuals who traded for at least 30 days (a total of 794,880 individual-day observations). By doing so, the sample becomes balanced across individuals.[7]

For each individual-day we have the gross result obtained from day-trading, $Result_{i,t}$, which is computed in dollars.[8] We define $Quit_{i,t} = 1$ if day t is individual's i last day of day-trading and $Quit_{i,t} = 0$ for the 19 days preceding the last one.

We want to estimate the probability of $Quit_{i,t} = 1$ as a function of $Result_{i,t}$. To do this, we separate the individual-day observations into bins relative to $Result_{i,t}$ and compute the average of $Quit_{i,t}$ and its 95% confidence band within each bin. We define 20 ten-dollar bins around zero: from -\$100 to -\$90, -\$90 to -\$80, ..., +\$80 to +\$90, and +\$90 to +\$100 ($Result_{i,t}$ is between -\$100 and +\$100 in 76% of the 794,880 individual-day observations). Figure 1 presents the result.

[Figure 1 about here]

Figure 1 shows the probability of $Quit_{i,t} = 1$ is a discontinuous function of $Result_{i,t}$. Since winning or losing a dollar reveals virtually the same information about an individual's ability, this discontinuity would not be expected in a world of Bayesian agents

[7]Results are very robust to changes in the time window.

[8]We use the average exchange rate in the period, 3.02 reais per dollar.

with no limits to processing information.[9]

Interestingly, the discontinuity at zero dwarfs any other effect on quitting. Whether an individual obtains a positive or a negative result on a given day determines the decision to continue or quit day-trading. The amount won or lost does not seem to matter. The probability of a day with a small loss (up to -\$10) being their last day of day-trade, considering their previous 20 days, is about 7.0%. In turn, the probability of a day with a small gain (up to +\$10) being their last day of day trade is about 4.0%. Since results are gross, the first bin on the gains region may actually also include negative net results. If we ignore this first bin and, instead, look at the second one (positive gross results from +\$10 to +\$20), the probability of quitting falls below 3.0%.

Figure 1 points to the sheer proportion of days with a positive result as the key statistic to explain quitting behavior. To confirm this, we estimate the following panel regression, using all individual-day observations starting on the 31st day of day trade of each individual (the first day we may observe quitting in the sample since the 39,744 individuals day-traded for at least 30 trading days):

$$Quit_{i,t} = \beta_1 TotResult_{i,t} + \beta_2 Prop_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t} \tag{1}$$

where $Quit_{i,t}$ is equal to 1 if t is the last day of day trade of individual i and zero otherwise, $TotResult_{i,t}$ is the total financial gross result of individual i from day 1 to day t (in thousands of dollars), $Prop_{i,t}$ is the proportion of days with a positive gross result from day 1 to day t, μ_i are individual fixed-effects (a constant for each individual) and γ_t are day-trading days fixed-effects (a constant for the 31st day of day trade of each individual, another for the 32nd, and so on).

[9] Interestingly, Ben-David, Birru, and Prokopenya (2018) also document discontinuities around zero returns when examining the effects of past-week performance of Forex day traders on future risk-taking measures such as trade size and the number of trades.

By employing trading days fixed-effects, we are estimating, for a given trading day (for instance, the 50th), the chances of an individual quitting day-trading on that specific trading day – across all individuals who have persisted until that day (at least). If individuals look at their total financial result until that day to decide to quit or continue day-trading, we should find β_1 negative and significant. If individuals look at their proportion of days with a positive result until that day, we should find β_2 negative and significant.

Importantly, by including individual fixed effects, we consider omitted variables at the individual level that can affect the quitting decision, such as income, overall trading skill, IQ, etc. Table 2 presents the estimates of equation 1.

[Table 2 about here]

Table 2 shows that the coefficient on individuals' cumulative result is statistically significant only when we do not control for the proportion of wins. As shown in column 3, what really matters is the proportion of days they have got a positive gross result. An increase of 10 percentage points in this proportion decreases the probability of quitting in 0.58 percentage point (a large effect given that the average of $Quit$ is 1.29%).

3.1 Intensive margin: Number of days until next day trade

In Table 2, the dependent variable $Quit_{i,t}$ is equal to 1 if t is the last day of day trade of individual i and zero otherwise. We could perceive this as an extensive margin of individuals behavior, while the intensive margin would be the number of days until the next day of day trade.

If we consider this intensive margin as the dependent variable of regression (1), we also find that the sheer proportion of profitable days, and not the actual financial result, explains individuals behavior. This is shown in Table 3.

[Table 3 about here]

Column 3 of Table 3 shows that an individual with a larger proportion of profitable days until t will day-trade again sooner. In turn, their actual financial result until day t does not explain $NumDays_{i,t}$ once we controll for $Prop_{i,t}$.

3.2 Recent vs. former proportion of profitable days

In Tables 2 and 3, we compute the proportion of profitable days of individual i from their first day of day trade until day t. We now show that the recent proportion of profitable days is more important to explain individuals quitting behavior than a proportion computed with days further in the past.

We estimate

$$Quit_{i,t} = \beta_1 RecentProp_{i,t} + \beta_2 FormerProp_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

where $RecentProp_{i,t}$ is the proportion of days with a positive gross result from day $t-9$ to day t, i.e., considering the last 10 days of day trade, and $FormerProp_{i,t}$ is the proportion of days with a positive gross result from day $t-19$ to day $t-10$, i.e., considering the 10 days before. Table 4 presents the results.

[Table 4 about here]

As shown in column 3 of Table 4, both recent and former proportions of profitable days explain quitting decision. However, the coefficient on the recent proportion is about 10 times larger. This is consistent with the recent proportion being easier to be recalled by individuals.

3.3 Who looks at the proportion of profitable days?

Among the 39,970 individuals in our sample, 90% are males, the average age is 36 (median 34), and the median number of different stocks they have purchased (not day-traded) during our sample period is 8 (10,585 individuals have only day-traded, i.e., have purchased no stock).

To understand whether the quitting behavior varies across different groups of individuals, we estimate regression (1) separated for males and females, individuals above and below the median age, and individuals above and below the median number of stocks purchased. Table 5 presents the results.

[Table 5 about here]

According to Table 5, the proportion of profitable days explains individual's quitting decision for all groups of individuals. However, for women, younger and more diversified individuals, the coefficient of $TotResult$ is also statistically significant, indicating that these individuals also look at their actual financial result when deciding to quit day-trading.

3.4 Robustness

Day-trading profits are likely to be upward-biased in the case of stocks. This is because some stock purchases that were not supposed to be day trades will appear as profitable day trades in our sample. Due to the disposition effect, individuals who bought an asset with the intention of holding it are more likely to close the position on the same day if the stock price rises hours after the purchase.

Although this would generate an upward bias in the performance measures for day-trading stocks, it is unclear how this would bias our conclusion that individuals' decisions to continue day-trading are explained by the proportion of profitable days and not by their actual overall financial result. Nonetheless, we now show that this conclusion remains the same if we consider only day-trading in future contracts, where the issue is not relevant.

In the context of day-trading futures contracts, leveraging far exceeds the trader's actual capital, often surpassing 400 times the amount deposited in the brokerage house. Actually, this is what attracts individuals to day-trade future contracts — for the 39,744 individuals in our main sample, 80.4% of their day trades are in future contracts, and 19.6% are in stocks. The leverage in future contracts implies that individuals cannot carry positions overnight. Hence, the vast majority of trades in future contracts should indeed be day trades from the start.

Table 6 shows results when compute day traders' daily results in future contracts only. The estimates are very similar to those in Table 2.

[Table 6 about here]

As an additional robustness analysis we consider a more restrictive filter for the selected individuals. We use 2012, 2013, and 2014 to identify the first day of day trade. That is, we say an individual began to day-trade on a given day of 2015 or later if we see no day-trading activity from them before that day. Moreover we exclude individuals who have day-traded any time 2018 to define the last day of day trade.[10] We end up with 23,428 individuals. Estimates are again similar to those in Table 2, as shown in Table 7.

[10]As described in Section 2, our original dataset goes from 2012 to 2018 and we say an individual began to day-trade on a given day of 2013 or later if we see no day-trading activity from them before that day. That is, we use the year of 2012 to identifying the first day individuals day-trade. Moreover, also as described in Section 2, we exclude individuals who have day-traded in the last two months of our sample (November and December 2018), for whom our sample may be censored, i.e., the last day of day trade that we observe may not be really the last.

[Table 7 about here]

4 Disposition effect and asymmetric daily results

The previous section shows that individuals' decisions to quit day-trading are explained mainly by their simple proportion of days with a positive result, not by their actual total financial result. We now show that the proportion of winning days is a biased measure of day-trading performance.

First, we show that the distribution of individuals' daily results is highly skewed to the left. Day traders have more winning days than losing days. However, since their daily losses are larger than their daily gains, they display a negative overall result.

We then relate the asymmetric distribution of daily results to the disposition effect using two different methods. First, we use intraday data available for a subsample of individuals. Second, we develop a stylized model of a trading day that allows us to estimate agents' trading skills and disposition effects from data on daily results.

4.1 Asymmetric daily results

For most individuals, daily losses are larger than daily gains; the distribution of daily results is skewed to the left. As such, even though $Prop > 50\%$, day-trading can lead to an overall financial loss.

The distribution of $Result_{i,t}$ across all individual-day observations is indeed strongly negatively skewed. It has an average of -24 dollars and a median of 2 dollars; the 1st percentile is $-1,589$ dollars while the 99th percentile is $1,112$ dollars, and the 5th percentile is -359 dollars while the 95th percentile is 310 dollars.

However, since different individuals trade different volumes, evaluating the skewness of $Result_{i,t}$ is not ideal. We then create a standardized measure for $Result_{i,t}$, called

$StdResult_{i,t}$, which is given by $Result_{i,t}$ divided by the average of the absolute value of $Result_{i,t}$ during the previous 30 days of day trade for individual i. The interpretation of $StdResult_{i,t}$ is straightforward: if $StdResult_{i,t} = 2$, individual i won on day t a value that is two times the average value he has been winning or losing in the recent past; if $StdResult_{i,t} = -2$, he lost on day t a value that is two times the average value he has been winning or losing in the recent past.

The skewness of *StdResult* is also negative. It has an average of -0.2 and median of 0.05, the 1st percentile is -6.9 while the 99th percentile is 3.8, and the 5th percentile is -2.9 while the 95th percentile is 1.9.

It is also illustrative to compute the skewness of *Result* within each individual and evaluate its distribution. Accordingly, Figure 2 plots the distribution across individuals of the skewness of their gross daily results. Out of the $39,744$ individuals, $32,810$ display negative skewness in their gross daily results. The median skewness across the $39,744$ individuals is -1.40, and the average skewness is -1.72.[11]

[Figure 2 about here]

The strong negative skewness of daily results leads to individuals profiting on most of the days but, at the same time, losing money by day-trading.

4.2 The disposition effect generates skewness

Individuals with the disposition effect tend to call it a day if the initial trades are profitable but are likely to keep on day-trading if they are losing. As a result, they may recover their losses but may also lose more. Hence, the disposition effect will

[11] The 1st percentile is -9.25, the 5th percentile is -5.79, the 95th percentile is 1.36, and the 99th percentile is 3.41. Hence, the skewness distribution is also negatively skewed (-1.00).

mechanically inflate the proportion of days with a positive result — but also raise the size of the losses.

In this section, we first show a strong disposition effect among day traders, consistent with previous literature (see Linnainmaa, 2003, Linnainmaa, 2005, Jordan and Diltz, 2003, and Heimer, 2016). We then show that, as expected, individuals with a stronger disposition effect tend to present higher $Prop$ and a more negative skewness in their daily results.

To directly measure the disposition effect among day traders, we obtained a subsample with the entire intraday trading activity of 3,980 individuals from our original dataset from CVM. This subsample was randomly selected from the 39,744 individuals in our full dataset, subject to including 10% of individuals from each of the 12 groups in Table 1. For each individual, we have the instrument (futures contract or stock) traded, the quantities purchased and sold, the corresponding prices, and the timestamp of each deal. Overall, we have 13,130,771 different deals. On average, there were 22 deals at the id-instrument-day level, resulting in 594,165 different id-instrument-day day trades. At the id-day level, we have 430,805 different trading days, with an average of 108 days with a day trade per individual.

First, we verify whether day traders display the disposition effect using the intraday data set. We follow Heimer (2016) and estimate a survival function from a Cox proportional hazard model in which the outcome variable is the total duration of a day trade (in minutes) from individual i in day d. We compute the duration of a day trade as the time elapsed from the day's first deal to its last deal. The average duration of the 430,805 different day trades is 238 minutes, the 25th percentile is 80 minutes, the median is 235 minutes, and the 75th percentile is 385 minutes. We then condition the total duration of a day trade on a dummy variable indicating whether the day trade from individual i on day d was profitable. We estimate the following hazard function:

$$h_{i,d}(t) = h_0(t)\exp(\beta Gain_{i,d} + X_i'\gamma) \tag{3}$$

where X_i denote the control variables that we include in the model: the total number of day trades by individual i and the total profit obtained by individual i.

The results from the Cox proportional hazard model confirm that day traders display a disposition effect. The estimate for β in Equation (3) is 0.176, significantly larger than zero with a t-statistic of 57. This coefficient implies that at any given point, the probability of a day trader closing the position for the day is 19.2% higher if she is at a gain than if she is at a loss ($1.192 = \exp(0.176)$). Figure 3 shows the resulting survival function up until minute 240 (the median duration of a day trade is 235 minutes), which indicates the probability of a day trader continuing day-trading conditional on having a gain or a loss.

[Figure 3 about here]

Next, we examine the extent to which day traders with a higher "*Prop*" also tend to display a stronger disposition effect and a more negative skewness in their daily results using this intraday dataset. To do so, we estimate the Cox proportional hazard model for each individual in our subsample. Table 8 presents the same summary statistics as before with the addition of columns 6 and 7. Column 6 shows the average skewness across day traders of *Result*, computed as before using all individuals' daily gross profits in US dollars. Column 7 shows the average across all point estimates of the hazard rate to closing a position conditional on a profitable day – a positive coefficient indicates a disposition effect.

[Table 8 about here]

First, we can see that the overall patterns observed in the full sample are also observed in this subsample with 10% of the number of individuals, which is reassuring. As before, going from group 1 to group 12, the fraction of individuals with positive profits declines (column 4), but the average fraction of individuals that profit on more than 50% of their trading days increases (column 5), and the average skewness decreases almost monotonically (column 6). Finally, the average estimates of the hazard rate increase as we move from lower to higher groups, implying the latter have a higher disposition effect. In the first four groups, the average estimates are 0.18, 0.12, 0.19, and 0.19, while in groups 9, 10, 11, and 12, they are 0.31, 0.24, 0.25, and 0.25, respectively.

To relate a day trader's proportion of profitable days, *Prop*, and the skewness of their daily results, *Skewness*, with their propensity to display the disposition effect, we run cross-sectional regressions across individuals. We control for the total gross profit obtained by the day trader and the number of days the individual has day-traded. Panel A of Table 9 shows the results for *Prop* and Panel B for *Skewness*.

[Table 9 about here]

Table 9 shows that the disposition effect is positively related to *Prop* and negatively related to *Skewness* across individuals. For instance, in Column 2 of Panel A, a change of 0.10 in the estimated D.E. coefficient is associated with an increase of 0.8% in the proportion of days with positive profit ($0.008 = 0.084 \times 0.10$). This result holds for individuals who have day-traded for more than 250 days (Group 12) and those within Group 1. In turn, Column 2 of Panel B shows that a change of 0.10 in the estimated D.E. coefficient is associated with a 0.09 lower skewness of daily results ($-0.09 = 0.923 \times 0.10$). This effect also holds within group 1 and within group 12.

4.3 A model to infer individuals' actual skill

We have shown that *Prop* is a biased measure of performance. We now develop and estimate a model to infer the counterfactual proportion of profitable days among day traders if they displayed no disposition effect.

4.3.1 The model

A day is divided into two periods. At the beginning of period 1, an individual makes a bet of size normalized to 1. At the end of period 1, they earn $y_1 = 1 \times x_1$, where x_1 is a draw from a $N(\mu, \sigma)$ distribution.[12] Parameters μ and σ determine the chances of obtaining a positive result and hence pin down their actual skill.

If $y_1 > 0$, the individual stops trading for that day, but may continue if $y_1 < 0$.

At the start of period 2, those who lost in the first period make a bet of size $-\alpha \times y_1$. It is proportional to the loss from period 1, where $\alpha \geq 0$ and will be estimated from data. The parameter α is a measure of the disposition effect since it captures the increase in their position after a negative result in the first period. If $\alpha = 0$, there is no disposition effect. At the end of period 2, they earn $y_2 = -\alpha \times y_1 \times x_2$, where x_2 is another independent draw from the same $N(\mu, \sigma)$ distribution. The total result from that day is thus given by

$$y = y_1 + y_2 = x_1 \left(1 - \alpha \times x_2 \mathbf{1}(x_1 \leq 0)\right),$$

where $\mathbf{1}(\cdot)$ denotes the indicator function.

We can decompose the expression above as follows. Let $f(z; \mu, \sigma)$ and $F(z; \mu, \sigma)$ denote the pdf and cdf, respectively, of the normal distribution with mean μ and standard deviation σ at $z \in \mathbb{R}$. Let $x_{(+)}$ denote the truncated normal distribution with

[12] The results are qualitatively the same if we assume a t-distribution instead.

parameters μ and σ on the interval $(0, \infty)$ with pdf

$$f_{(+)}(z; \mu, \sigma) = \frac{f(z; \mu, \sigma)}{1 - F(0; \mu, \sigma)} \mathbf{1}(z > 0).$$

Likewise, let $x_{(-)}$ denote the truncated normal distribution with parameters μ and σ on the interval $(-\infty, 0]$ with pdf

$$f_{(-)}(z; \mu, \sigma) = \frac{f(z; \mu, \sigma)}{F(0; \mu, \sigma)} \mathbf{1}(z \leq 0).$$

Finally, let B denote a random variable from a Bernoulli distribution with parameter

$$p = \mathbb{P}(x_1 > 0) = 1 - F(0; \mu, \sigma).$$

Then the distribution of the total result from day-trading on a given day can be alternatively expressed as

$$y = B \times x_{(+)} + (1 - B) \times [x_{(-)}(1 - \alpha x_2)]. \tag{4}$$

4.3.2 Estimation procedure

Next, we estimate parameters α, μ, and σ using day traders observed daily results and the Generalized Method of Moments (GMM) with the following moments: (i) $\mathbb{P}(y > 0)$, (ii) $\mathbb{E}(y)$, (iii) $\mathrm{Var}(y)$ and (iv) $\mathrm{Skew}(y)$. The closed-form expressions for the four moments of interest are:[13]

$$\mathbb{P}(y > 0) = 1 - \Phi(-\mu/\sigma) + \Phi(-\mu/\sigma)\left(1 - \Phi\left(\frac{1-\alpha\mu}{\alpha\sigma}\right)\right) \tag{5}$$

$$\mathbb{E}(y) = \mu(1-\alpha\mu) + (1-\Phi(-\mu/\sigma))\alpha\mu^2 + \alpha\sigma\mu\phi(-\mu/\sigma) \tag{6}$$

$$\mathbb{E}(y^2) = \mu^2 + \sigma^2 + \left(\Phi(-\mu/\sigma)(\mu^2+\sigma^2) - \mu\sigma\phi(-\mu/\sigma)\right]\left[\alpha^2(\mu^2+\sigma^2) - 2\alpha\mu\right] \tag{7}$$

$$\begin{aligned}\mathbb{E}(y^3) = {} & \mu^3 + 3\mu\sigma^2 + \left[\Phi(-\mu/\sigma)(\mu^3+3\mu\sigma^2) - \sigma(\mu^2+2\sigma^2)\phi(-\mu/\sigma)\right] \\ & \times \left[3\alpha^2(\mu^2+\sigma^2) - 3\alpha\mu - \alpha^3(\mu^3+3\mu\sigma^2)\right]\end{aligned} \tag{8}$$

where Φ and ϕ denote the cdf and pdf, respectively, of the standard normal distribution.

We can compute

$$Var(y) = \mathbb{E}(y^2) - \mathbb{E}(y)^2,$$

using Equations (6) and (7). Finally, we get

$$Skew(y) = \frac{\mathbb{E}(y^3) - 3\mathbb{E}(y)Var(y) - \mathbb{E}(y)^3}{Var(y)^{\frac{3}{2}}},$$

by combining $Var(y)$ with Equations (7) and (8).

With μ and σ, we can compute the probability of a positive result in period 1, $1 - F(0;\mu,\sigma)$, which is different than the probability of obtaining a positive result in the day (period 1 plus period 2) because it is not contaminated by the disposition effect. We refer to the probability of obtaining a positive result in period 1 as the 'actual skill'.

Since we consider individuals who trade different volumes, our measure of results is the daily gross profit of each day trader on each day divided by the average of their absolute gross profit over the past 30 trading days (i.e., *StdResult*, as defined in Section 4.1).

[13] see Appendix B for the derivation.

4.3.3 Estimation results

Table 10 shows the estimates considering all 39,744 day traders and their results for days 31st, 32nd, and so on.

[Table 10 about here]

The estimate of α is 0.489, indicating that day traders display a strong disposition effect: on average, a trader with a negative result bets an extra amount close to half of their losses.

Table 10 shows that the estimated probability of winning in period 1 ('model's skill', given by $1 - F(0; \hat{\mu}, \hat{\sigma})$) equals 0.467. This can interpreted as the odds of winning on a day in the absence of the disposition effect. In contrast, the biased skill, $Prop$, is 0.523. The distance between the biased and the actual skill, i.e., the bias from the disposition effect, is rather large, equal to 5.6 percentage points.

The table also shows an alternative estimate of day traders' skill based on our intraday data from a subset of day trades discussed in section 4.2 (Intraday data's skill). For each day trader's transaction, we calculate the result after 20 minutes.[14] This estimated measure of skill equals 0.478. While this refers to each single decision, the estimate from the model refers to the set of trades that would occur without the disposition effect. Hence, the estimates are not directly comparable, but both should be either higher or lower than 50%, and the measure based on a single trade should be closer to 50%. This is exactly what we find.

It is also illustrative to examine how the actual and biased skill evolve for investors who persisted in day-trading. To do that, we estimate the model parameters for the

[14]Specifically, we compute the cumulative return from the purchasing or selling price up until 20 minutes in the future, multiplying by minus one the cumulative return if a sale occurred. We exclude deals closed within the last 20 minutes of the trading day. Then, we determine the fraction of all profitable transactions at this time horizon. We use a 20-minute horizon because it represents the unconditional average duration of a day trader's deal.

individuals in Group 12, as defined in Section 3, from day 31 to day 60, 61 to 90, and so on up to day 241 to the last one. Table 11 presents the results.

[Table 11 about here]

The actual skill estimate $1 - F(0; \hat{\mu}, \hat{\sigma})$ remains flat around 47%, reflecting a roughly constant ratio μ/σ. Reassuringly, the true skill estimated with the sub-sample of investors for whom we observed their intraday activity is also constant, around 48%. Both measures are not supposed to be the same, but should display similar patterns. The finding that day traders do not learn with experience is consistent with previous research – see Chague, De-Losso, and Giovannetti (2019) and Barber et al. (2020).

Second, we find a very large increase in α. The coefficient doubles over time, going from 0.386 to 0.796. Accordingly, the biased measure of skill also increases with experience. It begins at 0.515 and reaches a whopping 0.567 in the last bin. Since day traders look at the biased skill to decide when to stop, a growing α creates a perverse dynamics for the learning process about their own skill.

5 Concluding remarks

This paper investigates all retail day trading activity in Brazil from 2012 to 2018. It shows that (i) individuals use a simple counting heuristic (the frequency of profitable trading days) to decide whether to continue trading and (ii) display a strong disposition effect. As a result, their learning about their own trading skills is biased. These findings shed light on the drivers under individual traders' overconfidence.

Our study focuses on day trading, but there is reason to believe this behavior extends to other trading activities. This is because accurately measuring day trading results requires only adding up daily profits, while evaluating the performance of a portfolio is a much harder task, as it requires considering risk and comparing returns to benchmarks.

Our conclusions matter for policy. Day trading and swing trading are booming in many countries. Informing individuals about their actual odds of success might deter many of them from spending time and money on an endeavor bound to fail.[15]

[15]The Brazilian exchange, B3, should take note. At present, they do precisely the opposite by showing on their website the proportion of day traders that profit each day (see, for instance, a recent report available here). It is a simple statistic to show, they would argue. It is indeed, and that is why it has the power to confuse hapless individuals in search of a thrilling way to make a living.

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A Figures and Tables

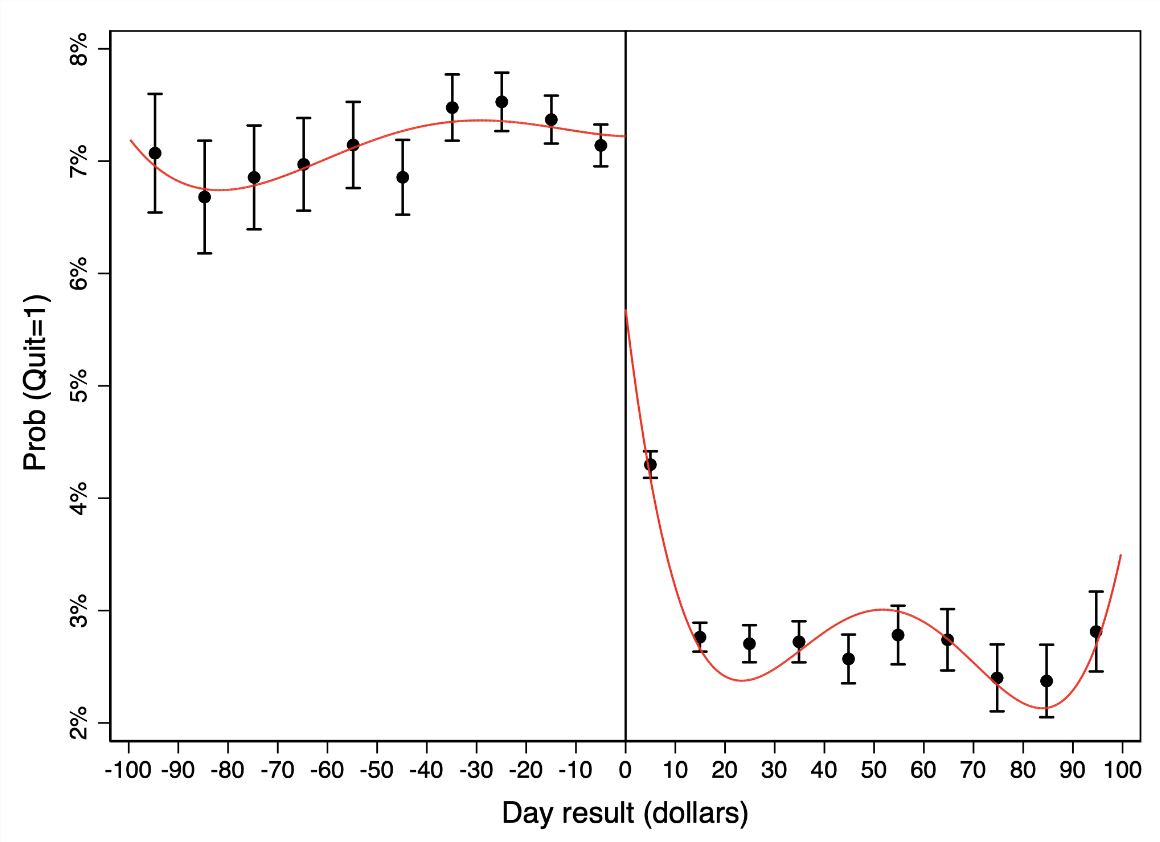

Figure 1: This figure plots the probability of quitting day-trading on a given day as a function of the gross result (*Result*) of that day. A polynomial (of order 4 with a triangular kernel) is fitted on the negative and positive regions to approximate the conditional mean functions.

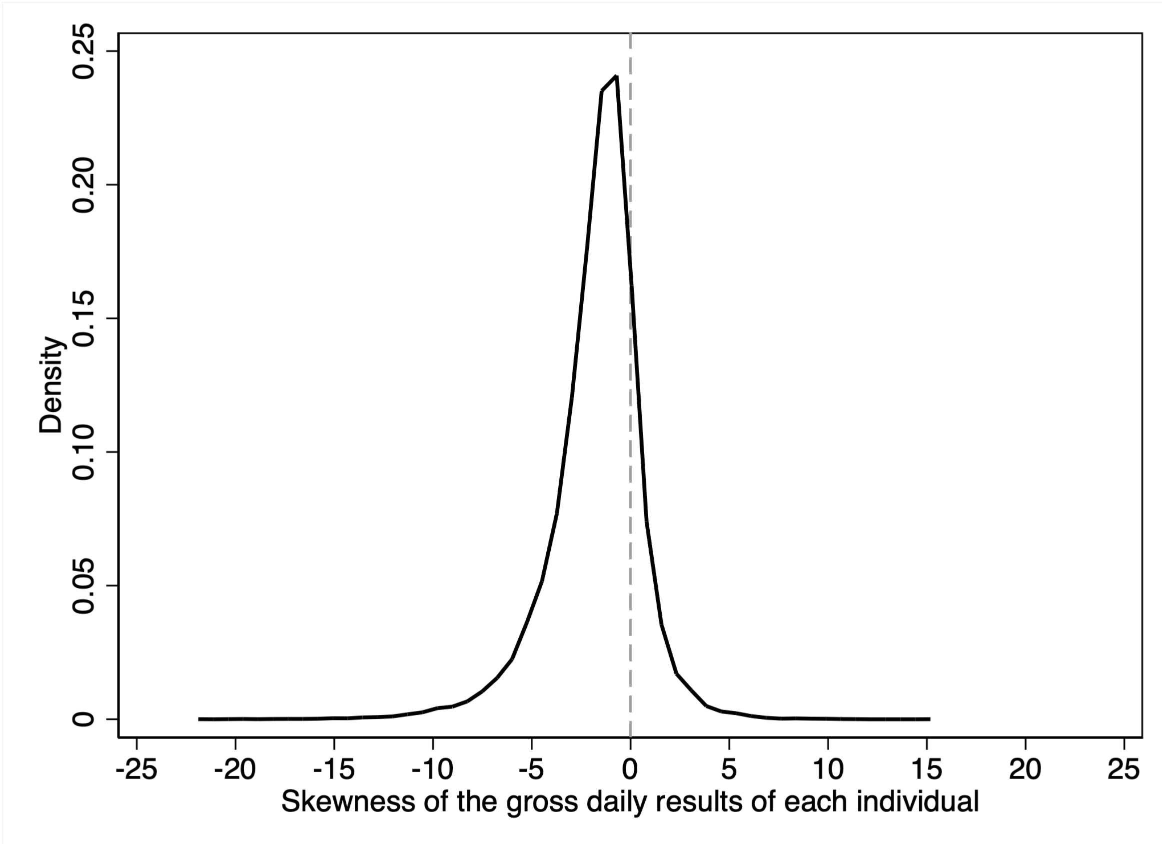

Figure 2: This figure plots the distribution across individuals of the skewness of their gross daily results.

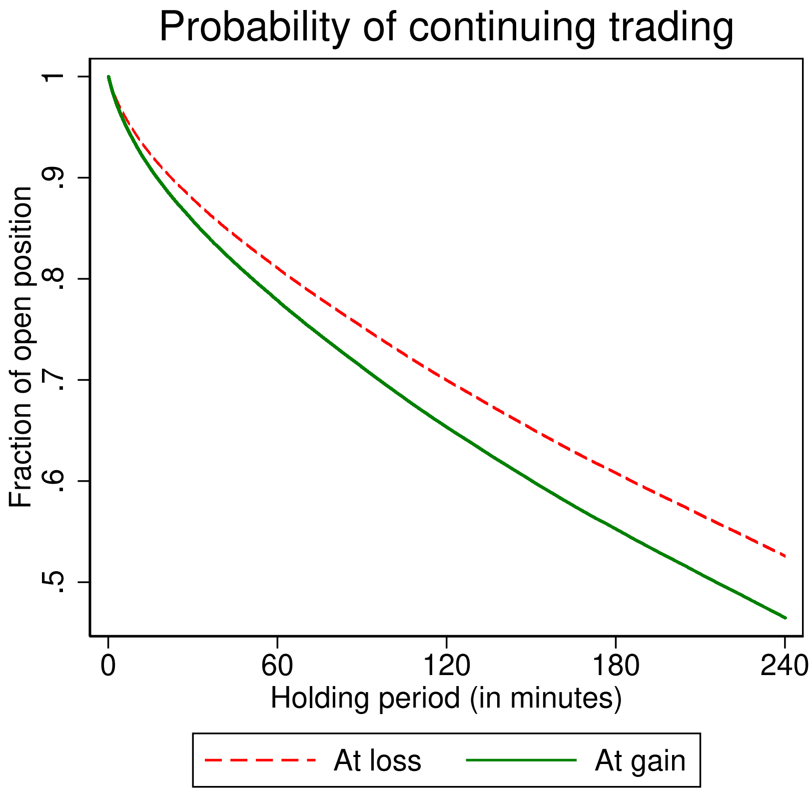

Figure 3: This figure plots the estimated survival function from a Cox proportional hazard model in which the outcome variable is the total duration of a day trade (in minutes), and the conditioning variable is a dummy variable indicating whether the day trade was profitable or not.

Table 1: Number of individuals per group and some statistics

We divide individuals into 12 groups according to their number of days of day trade. Group 1 contains individuals who day-traded from 31 to 50 days, Group 2 contains individuals who day-traded from 51 to 70 days, and so on, up to Group 12 that contains individuals who day-traded for more than 250 days. This table presents the number of individuals in each group, along with the proportion of individuals in the group with positive total gross result and the proportion of individuals in the group who presented positive result in more than 50% of the days of day trade.

Group (1)	Days of day trade (2)	Number of individuals (3)	% of ind. with total gross result > 0 (4)	% of ind. with days with + result > 50% (5)
1	[31; 50]	12,915	24	44
2	[51; 70]	7,018	22	45
3	[71; 90]	4,653	20	47
4	[91; 110]	3,254	18	46
5	[111; 130]	2,276	17	48
6	[131; 150]	1,748	18	51
7	[151; 170]	1,412	15	49
8	[171; 190]	1,105	16	53
9	[191; 210]	965	16	52
10	[211; 230]	704	16	57
11	[231; 250]	567	13	58
12	more than 250	3,127	15	61
all individuals		39,744	20	48

Table 2: Quitting day-trading on day t

We estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), across the 39,744 individuals in the sample, employing trading day and individual fixed-effects. The dependent variable is $Quit_{i,t}$, which is equal to 1 if day t is the last day of day trade of individual i and zero otherwise. The explanatory variables are $TotResult_{i,t}$, the total financial result of individual i from day 1 to day t (in thousands of dollars) and $Prop_{i,t}$, the proportion of days with a positive gross result from day 1 to day t (a variable from 0 to 1). Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

		$Quit_{i,t}$	
	(1)	(2)	(3)
$TotResult_{i,t}$	-0.001***		-0.001
	(-3.53)		(-1.50)
$Prop_{i,t}$		-0.058***	-0.058***
		(-23.10)	(-22.94)
Day fixed-effect	✓	✓	✓
Ind. fixed-effect	✓	✓	✓
Obs	3,075,869	3,075,869	3,075,869
Adj. R2	0.05	0.05	0.05

Table 3: Number of days until next day trade

We estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), across the 39,744 individuals in the sample, employing trading day and individual fixed-effects. The dependent variable is $NumDays_{i,t}$, the number of days until the next day trade by individual i, i.e., the number of days between observations t and $t+1$ for individual i. The explanatory variables are $TotResult_{i,t}$, the total financial result of individual i from day 1 to day t (in thousands of dollars) and $Prop_{i,t}$, the proportion of days with a positive gross result from day 1 to day t (a variable from 0 to 1). Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$NumDays_{i,t}$		
	(1)	(2)	(3)
$TotResult_{i,t}$	-0.002*		0.001
	(-1.81)		(1.10)
$Prop_{i,t}$		-12.10***	-12.13***
		(-24.66)	(-24.61)
Day fixed-effect	✓	✓	✓
Ind. fixed-effect	✓	✓	✓
Obs	3,036,160	3,036,160	3,036,160
Adj. R2	0.06	0.06	0.06

Table 4: Recent vs. former proportion of profitable days

We estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), across the 39,744 individuals in the sample, employing trading day and individual fixed-effects. The dependent variable is $Quit_{i,t}$, which is equal to 1 if day t is the last day of day trade of individual i and zero otherwise. The explanatory variables are $RecentProp_{i,t}$, the proportion of days with a positive gross result from day $t-9$ to day t, i.e., considering the last 10 days of day trade, and $FormerProp_{i,t}$, the proportion of days with a positive gross result from day $t-19$ to day $t-10$, i.e., considering the 10 days before. Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$Quit_{i,t}$		
	(1)	(2)	(3)
$RecentProp_{i,t}$	-0.023***		-0.023***
	(-38.91)		(-38.94)
$FormerProp_{i,t}$		-0.003***	-0.002***
		(-5.79)	(-3.80)
Day fixed-effect	✓	✓	✓
Ind. fixed-effect	✓	✓	✓
Obs	3,075,869	3,075,869	3,075,869
Adj. R2	0.06	0.05	0.06

Table 5: The importance of *Prop*: Heterogeneity across individuals

We estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), across the 39,744 individuals in the sample divided in groups (gender, age, and number of stocks purchased), employing trading day and individual fixed-effects. The dependent variable is $Quit_{i,t}$, which is equal to 1 if day t is the last day of day trade of individual i and zero otherwise. The explanatory variables are $TotResult_{i,t}$, the total financial result of individual i from day 1 to day t (in thousands of dollars) and $Prop_{i,t}$, the proportion of days with a positive gross result from day 1 to day t (a variable from 0 to 1). Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: $Quit_{i,t}$					
	Gender		Age		Num of Stocks	
	Male	Female	< med.	> med.	< med.	> med.
	(1)	(2)	(3)	(4)	(5)	(6)
$TotResult_{i,t}$	-0.001	-0.001***	-0.001**	-0.001	-0.001	-0.001**
	(-0.61)	(-2.88)	(-2.39)	(-0.62)	(-0.30)	(-2.19)
$Prop_{i,t}$	-0.055***	-0.074***	-0.087***	-0.046***	-0.087***	-0.040***
	(-21.81)	(-10.81)	(-19.20)	(-18.52)	(-21.37)	(-16.26)
Day fixed-effect	✓	✓	✓	✓	✓	✓
Ind. fixed-effect	✓	✓	✓	✓	✓	✓
Obs	2,705,026	274,312	1,136,732	1,938,970	1,378,688	1,696,871
Adj. R2	0.05	0.05	0.05	0.05	0.05	0.05

Table 6: Quitting day-trading on day t (only future contracts)

Considering only future contracts, we estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), employing trading day and individual fixed-effects. The dependent variable is $Quit_{i,t}$, which is equal to 1 if day t is the last day of day trade of individual i and zero otherwise. The explanatory variables are $TotResult_{i,t}$, the total financial result of individual i from day 1 to day t (in thousands of dollars) and $Prop_{i,t}$, the proportion of days with a positive gross result from day 1 to day t (a variable from 0 to 1). Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

		$Quit_{i,t}$	
	(1)	(2)	(3)
$TotResult_{i,t}$	-0.001***		-0.001
	(-2.68)		(-0.94)
$Prop_{i,t}$		-0.066***	-0.066***
		(-23.58)	(-23.44)
Day fixed-effect	✓	✓	✓
Ind. fixed-effect	✓	✓	✓
Obs	2,449,827	2,449,827	2,449,827
Adj. R2	0.05	0.05	0.05

Table 7: Quitting day-trading on day t (less individuals)

We estimate panel regressions at the individual-day level (day equal to 31 for the 31st day of day trade of the individual, 32 for the 32nd day, and so on), employing trading day and individual fixed-effects. The dependent variable is $Quit_{i,t}$, which is equal to 1 if day t is the last day of day trade of individual i and zero otherwise. The explanatory variables are $TotResult_{i,t}$, the total financial result of individual i from day 1 to day t (in thousands of dollars) and $Prop_{i,t}$, the proportion of days with a positive gross result from day 1 to day t (a variable from 0 to 1). Standard errors are double clustered at both the individual and day levels, and t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

		$Quit_{i,t}$	
	(1)	(2)	(3)
$TotResult_{i,t}$	-0.001***		-0.001
	(-3.51)		(-0.94)
$Prop_{i,t}$		-0.092***	-0.092***
		(-20.96)	(-20.87)
Day fixed-effect	✓	✓	✓
Ind. fixed-effect	✓	✓	✓
Obs	1,463,688	1,463,688	1,463,688
Adj. R2	0.05	0.05	0.05

Table 8: Number of individuals per group and some statistics: Intraday subsample

The table shows some descriptive statistics based on intraday trading information for a subsample of 3,980 day traders. As before, we divide them into 12 groups according to their number of days of day-trading. Group 1 contains individuals who day-traded from 31 to 50 days, Group 2 contains individuals who day-traded from 51 to 70 days, and so on, up to Group 12, which contains individuals who day-traded for more than 250 days. Column (2) presents the number of individuals in each group. Column (3) shows the average number of day-trading days across individuals. Column (4) displays the fraction of individuals with a positive gross profit. Column (5) indicates the fraction of individuals with more than 50% of day-trading days with a positive profit. Column (6) shows the average skewness across individuals computed using all individuals' daily gross profits. Finally, column (7) show the average across all estimates of the hazard rate to closing a position conditional on a profitable day – a positive coefficient indicates Disposition Effect.

Group	N. of individ.	Number of days	Positive profit	Positive days	Skew.	D.E. coeff.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	1292	39	0.25	0.46	-1.16	0.18
2	702	60	0.19	0.44	-1.44	0.12
3	466	80	0.23	0.47	-1.61	0.19
4	326	100	0.17	0.46	-1.85	0.19
5	228	120	0.18	0.46	-1.96	0.24
6	175	141	0.20	0.51	-1.99	0.19
7	142	161	0.16	0.46	-2.28	0.21
8	111	181	0.15	0.47	-2.28	0.21
9	97	200	0.18	0.63	-2.45	0.31
10	71	220	0.15	0.52	-2.66	0.24
11	57	241	0.09	0.54	-2.46	0.25
12	313	398	0.15	0.59	-2.95	0.25
All	3980	108	0.21	0.48	-1.69	0.19

Table 9: Fraction of profitable days and the disposition effect

The table shows the estimates of regressing $Prop_i$, the fraction of positive days for an individual in Panel A, and $Skewness_i$, computed using all individuals' i daily gross profits in Panel B, on DE_i, a measure of the disposition effect for individual i. DE_i is the estimated hazard rate of a Cox proportional hazard model in which the outcome variable is the total duration of a day trade (in minutes), and the conditioning variable is a dummy variable indicating whether the day trade was profitable or not. We winsorized the estimated coefficients at 1% and 99%. We also include as control variables *Number of days*, the total number of days individual i day-traded in 100s, and *Gross profit*, the total accumulated profit of individual i in 100,000s US dollars. Columns 1 and 2 consider all 3,980 individuals in the intraday subsample. Columns 3 and 4 consider only day traders in Group 1. Columns 5 and 6 consider only day traders in Group 12. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	All groups		Only Group 1		Only Group 12	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Prop*						
D.E. coeff	0.084***	0.084***	0.052***	0.058***	0.136***	0.136***
	(13.97)	(14.23)	(5.03)	(6.13)	(7.06)	(7.02)
Number of days		0.013***		0.170**		0.012***
		(6.66)		(2.39)		(2.90)
Gross profit		0.150***		0.984***		0.054***
		(5.01)		(6.21)		(3.00)
Constant	0.495***	0.484***	0.500***	0.438***	0.506***	0.464***
	(194.08)	(143.13)	(99.05)	(15.43)	(60.50)	(28.10)
Adjusted R-squared	0.06	0.10	0.02	0.13	0.14	0.20
Observations	3980	3980	1292	1292	313	313
Panel B: *Skewness*						
D.E. coeff	-0.989***	-0.923***	-0.636***	-0.558***	-1.875**	-1.835**
	(-11.89)	(-11.66)	(-6.39)	(-5.93)	(-2.46)	(-2.47)
Number of days		-0.390***		-1.127		-0.256
		(-7.37)		(-1.45)		(-1.60)
Gross profit		2.588***		10.291***		1.150***
		(5.38)		(5.87)		(2.88)
Constant	-1.487***	-1.015***	-1.032***	-0.547*	-2.476***	-1.319**
	(-36.96)	(-17.99)	(-19.43)	(-1.80)	(-8.35)	(-2.36)
Adjusted R-squared	0.03	0.11	0.03	0.12	0.03	0.07
Observations	3980	3980	1292	1292	313	313

Table 10: GMM estimation of the parameters of the model

This table presents the estimated value of the parameters of the model (μ, α, and σ) for the whole sample. Estimation is done via two-step GMM, and the efficient weighting matrix is used. Standard errors are in parenthesis. We also report the biased measure of skill, i.e., the proportion of days with positive result, observed directly from the data, as well as two measures of the true skill, one computed from the parameters as $1 - F(0; \hat{\mu}, \hat{\sigma})$, and the other using intraday data from a subsample of day traders.

	Estimates
μ	-0.147
	(0.001)
α	0.489
	(0.006)
σ	1.802
	(0.0168)
Model's skill	0.467
Intraday data's skill	0.478
Biased skill ($Prop$)	0.523

Table 11: Biased and real measures of skill for Group 12 over time

For each of the specified intervals of days described below, we estimate the parameters μ, α, and σ using individuals from Group 12, as defined in Section 3. We also report the biased measure of skill, i.e., the proportion of days with positive result, observed directly from the data, as well as two measures of the true skill, one computed from the parameters as $1 - F(0; \hat{\mu}, \hat{\sigma})$, and the other using intraday data from a subsample of day traders.

Days	μ		α		σ		Model's	Data's	Pollut.
window	est.	std.	est.	std.	est.	std.	skill	skill	skill
$[31; 60]$	-0.136	(0.005)	0.386	(0.038)	1.949	(0.149)	0.472	0.479	0.515
$[61; 90]$	-0.137	(0.005)	0.515	(0.013)	1.667	(0.032)	0.467	0.481	0.524
$[91; 120]$	-0.128	(0.005)	0.569	(0.014)	1.628	(0.029)	0.469	0.480	0.534
$[121; 150]$	-0.118	(0.004)	0.632	(0.013)	1.540	(0.021)	0.469	0.481	0.541
$[151; 180]$	-0.113	(0.004)	0.667	(0.013)	1.543	(0.02)	0.471	0.481	0.549
$[181; 210]$	-0.125	(0.004)	0.711	(0.019)	1.527	(0.028)	0.467	0.481	0.551
$[211; 240]$	-0.111	(0.004)	0.758	(0.018)	1.501	(0.026)	0.471	0.485	0.561
$[241, last]$	-0.113	(0.002)	0.796	(0.013)	1.516	(0.021)	0.470	0.483	0.567

B Computing the moments of the model

In this section, the goal is to show how the desired moments of the normalized daily profits, y, can be computed using only moments from $x_{(+)}$, $x_{(+)}$ and x_2 by using the characterization from Equation (4).

For each moment of interest, we first derive the moment equation for a general distributional specification for x_1 and x_2. Under the normal specification, the moment equations have closed-form expressions, based on the moments of the truncated normal distribution. These are also computed below. A recursive derivation of the moments of the truncated normal distribution can be found in Orjebin (2014) and Horrace (2014). The formulas for these moments are used throughout the rest of this Section.

In cases when closed-form solutions are not available, the moments are usually straightforward to compute numerically. Throughout the rest of this Section, we denote by $\phi(\cdot)$ and $\Phi(\cdot)$ and pdf and cdf, respectively, of the standard normal distribution.

B.1 Derivation of $\mathbb{P}(y > 0)$

First, notice that:

$$\begin{aligned}\mathbb{P}(y > 0) = &\quad \mathbb{P}(B = 1) + (1 - \mathbb{P}(B = 1)) \cdot \mathbb{P}(x_{(-)} \cdot (1 - \alpha x_2) > 0) \\ &= (1 - F(0; \mu, \sigma)) + F(0; \mu, \sigma) \cdot \mathbb{P}(x_{(-)} \cdot (1 - \alpha x_2) > 0) \qquad (9)\end{aligned}$$

Simplifying the last term above, we have that:

$$\mathbb{P}(x_{(-)} \cdot (1 - \alpha x_2) > 0) = \mathbb{P}(1 - \alpha x_2 < 0) = \mathbb{P}\left(x_2 > \frac{1}{\alpha}\right) = 1 - F(1/\alpha; \mu, \sigma)$$

Thus, Equation (9) only requires computations of the cdfs of the generalized and truncated normal distributions. Indeed, notice that a crucial step for this result is that the probability of getting a positive profit in the second trading session does not depend on the size of the losses during the first session. Since $x_{(-)}$ is negative with probability 1, we only need $(1 - \alpha x_2)$ to be positive to ensure that y is positive in this case.

Assuming the session profits follow a normal distribution, $p = 1 - \Phi(-\mu/\sigma)$ and Equation (9) simplifies to:

$$\mathbb{P}(y > 0) = 1 - \Phi(-\mu/\sigma) + \Phi(-\mu/\sigma)\left(1 - \Phi\left(\frac{1-\alpha\mu}{\alpha\sigma}\right)\right) \tag{10}$$

which is a simple function of the underlying parameters.

B.2 Derivation of $\mathbb{E}(y)$

After applying expectations in Equation (4) and using independence, we have:

$$\begin{aligned}\mathbb{E}(y) &= \mathbb{E}\left[B \times x_{(+)} + (1-B) \times (x_{(-)}(1-\alpha x_2))\right] \\ &= p\mathbb{E}(x_{(+)}) + (1-p)\mathbb{E}(x_{(-)})(1-\alpha\mathbb{E}(x_2)) \end{aligned} \tag{11}$$

Under the normality specification and using the properties of the truncated normal, we additionally have that:

$$\mathbb{E}[x_{(+)}] = \mathbb{E}[x_2|x_2 > 0] = \mu + \sigma\frac{\phi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)} \tag{12}$$

$$\mathbb{E}[x_{(-)}] = \mathbb{E}[x_2|x_2 < 0] = \mu - \sigma\frac{\phi(-\mu/\sigma)}{\Phi(-\mu/\sigma)} \tag{13}$$

Plugging these terms into Equation (11) and doing some algebraic manipulations yield:

$$\mathbb{E}(y) = \mu(1-\alpha\mu) + (1-\Phi(-\mu/\sigma))\alpha\mu^2 + \alpha\sigma\mu\phi(-\mu/\sigma) \tag{14}$$

which is again a simple expression of the original parameters.

B.3 Derivation of Var(y)

Let $\mathbb{E}(y) := \mu_y$. By expanding y^2 in Equation (4) and applying expectations, we have:

$$\begin{aligned} y^2 &= Bx_{(+)}^2 + (1-B)(1-\alpha x_2)^2 x_{(-)}^2 + 2B(1-B)x_{(+)}x_{(-)}(1-\alpha x_2) \\ \implies \mathbb{E}(y^2) &= p\mathbb{E}\left(x_{(+)}^2\right) + (1-p)\mathbb{E}\left(x_{(-)}^2\right)\mathbb{E}\left([1-\alpha x_2]^2\right). \end{aligned} \tag{15}$$

Notice that the cancellation of the third above term comes from $B(1-B) \equiv 0$. This fact will be used again when computing the skewness. Besides:

$$\mathbb{E}\left([1-\alpha x_2]^2\right) = \alpha^2\mathbb{E}(x_2^2) - 2\alpha\mathbb{E}(x_2) + 1 \tag{16}$$

After plugging Equation (16) into Equation (15), we have $\mathbb{E}(y^2)$, which in turn allows us to compute

$$Var(y) := \sigma_y^2 = \mathbb{E}(y^2) - \mathbb{E}^2(y),$$

where $\mathbb{E}(y)$ comes from Equation (11).

Under the normality specification, we have the following additional simplifications:

$$\mathbb{E}\left(x_{(+)}^2\right) = \mu^2 + \sigma^2 + \sigma\frac{\mu\phi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)} \tag{17}$$

$$\mathbb{E}\left(x_{(-)}^2\right) = \mu^2 + \sigma^2 - \sigma\frac{\mu\phi(-\mu/\sigma)}{\Phi(-\mu/\sigma)} \tag{18}$$

$$\mathbb{E}\left[(1-\alpha x_2)^2\right] = 1 - 2\alpha\mu + \alpha^2(\mu^2+\sigma^2) \tag{19}$$

Substituting these expressions into Equation (15) and canceling out terms, we can compute $\mathbb{E}(y^2)$ in terms of the parameters as:

$$\mathbb{E}(y^2) = \mu^2 + \sigma^2 + \left(\Phi(-\mu/\sigma)(\mu^2+\sigma^2) - \mu\sigma\phi(-\mu/\sigma)\right]\left[\alpha^2(\mu^2+\sigma^2) - 2\alpha\mu\right] \tag{20}$$

Finally, we are then able to compute $Var(y) = \mathbb{E}(y^2) - \mathbb{E}(y)^2$, where $\mathbb{E}(y)$ comes from Equation (14).

B.4 Derivation of Skew(y)

We now proceed to compute $\mathbb{E}(y^3)$ analogously to what was done before:

$$y^3 = Bx_{(+)}^3 + (1-B)x_{(-)}^3(1-\alpha x_2)^3 \implies$$

$$\mathbb{E}(y^3) = p\mathbb{E}\left(x_{(+)}^3\right) + (1-p)\mathbb{E}\left(x_{(-)}^3\right)\mathbb{E}\left([1-\alpha x_2]^3\right), \tag{21}$$

where the cross terms involving $B \times (1-B)$ cancel out as in Equation (15). By expanding the last term, we have:

$$\mathbb{E}\left([1-\alpha x_2]^3\right) = -\alpha^3\mathbb{E}(x_2^3) + 3\alpha^2\mathbb{E}(x_2^2) - 3\alpha\mathbb{E}(x_2) + 1. \tag{22}$$

By plugging Equation (22) into Equation (21) we can compute $\mathbb{E}(y^3)$, which in turn allows us to compute Skew(y) as:

$$\text{Skew}(y) = \mathbb{E}\left(\left[\frac{y-\mu_y}{\sigma_y}\right]^3\right) = \frac{\mathbb{E}(y^3) - 3\mu_y\sigma_y^2 - \mu_y^3}{\sigma_y^3}, \tag{23}$$

Under the normal specification, we again have the following additional simplifications:

$$\mathbb{E}\left(x_{(+)}^3\right) = \mu^3 + 3\mu\sigma^2 + \sigma\left[\frac{(\mu^2+2\sigma^2)\phi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)}\right] \tag{24}$$

$$\mathbb{E}\left(x_{(-)}^3\right) = \mu^3 + 3\mu\sigma^2 - \sigma\left[\frac{(\mu^2+2\sigma^2)\phi(-\mu/\sigma)}{\Phi(-\mu/\sigma)}\right] \tag{25}$$

$$\mathbb{E}\left[(1-\alpha x)^3\right] = 1 - 3\alpha\mu + 3\alpha^2(\mu^2+\sigma^2) - \alpha^3(\mu^3+3\mu\sigma^2) \tag{26}$$

Substituting these terms into Equation (21) and doing some algebraic manipulations leads us to:

$$\begin{aligned}\mathbb{E}(y^3) =& \mu^3 + 3\mu\sigma^2 + \left[\Phi(-\mu/\sigma)(\mu^3+3\mu\sigma^2) - \sigma(\mu^2+2\sigma^2)\phi(-\mu/\sigma)\right] \\ &\times \left[3\alpha^2(\mu^2+\sigma^2) - 3\alpha\mu - \alpha^3(\mu^3+3\mu\sigma^2)\right]\end{aligned} \tag{27}$$

We can then compute $Skew(y)$ as :

$$Skew(y) = \frac{\mathbb{E}(y^3) - 3\mathbb{E}(y)Var(y) - \mathbb{E}(y)^3}{Var(y)^{\frac{3}{2}}}, \tag{28}$$

where $\mathbb{E}(y)$ and $Var(y)$ are derived in the previous subsections.