The Asymmetric Rank Effect for Winning and Losing Portfolios

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Abstract

This paper shows that rank effects, investors' preferences for selling both their best and worst-ranked stocks, can be traced to different responses of investors as their portfolio performance fluctuates over time. When investors face poorly performing portfolios, they are predisposed to liquidate their best stocks; otherwise, their rank preferences attenuate and show some shift towards selling their worst positions. These findings are consistent with investors becoming more risk averse after observing underperforming portfolios. These results also shed light on the asymmetric V-shaped selling propensity, and on two prominent anomalies, the excess volatility of returns and the equity premium puzzle.

Keywords: rank effects, disposition effect, investor behavior

JEL Codes: G40, G41, D14

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1 Introduction

The traditional empirical framework for the study of investors' trading behaviour assumes that they engage in narrow framing by paying attention to each stock's gains and losses in isolation (e.g., Barberis and Xiong, 2012; Ingersoll and Jin, 2013; Frydman et al., 2014). Most of the empirical literature in asset prices ignores the fact that trading choices are made from sets. Pervasive effects of the choice set have been repeatedly demonstrated in consumer choice (e.g., Benartzi and Thaler, 2001; Kivetz et al., 2004; Lehmann and Pan, 1994; Simonson and Tversky, 1992). These findings suggest that judgments are relative and highlight the possibility that investors might have unstable or ill-formed preferences about their assets. More recently, some studies have taken into account the context provided by the choice set. Hartzmark (2015) offers what may be the most careful treatment on how the relative performance of stocks within the portfolio impacts trading decisions. He finds that investors are more likely to sell both the positions with the highest and the lowest performance ranks in their portfolio (a phenomenon he labels as the "rank effect"). Furthermore, he shows that both retail traders (including sophisticated investors) and mutual fund managers exhibit strong rank effects. Subsequent work has replicated these findings using diverse security brokerage data (An and Argyle, 2020; Frydman and Wang, 2020), and even when ranks were defined differently, by alphabetical order of company names (Frydman and Wang, 2020).

In this paper, I show that investors' preferences for selling both the best and the worst-ranked positions in the portfolio, observed in the cross section, can be traced to different responses of investors when their portfolio performance fluctuates over time.[1] Rank effects are asymmetric: when investors face portfolios with poor performance, they are predisposed to liquidate their best stocks; otherwise, their rank preferences attenuate and show some shift towards liquidating their worst positions. More broadly, the mechanisms behind the interaction effect between rank preferences and portfolio performance I document here can explain other perplexing features in retail trading data, such as the asymmetric V-shaped selling propensity in response to unrealized profits (i.e., the finding that the investors' selling probability increases as the magnitude of gains and losses increases, with a steeper slope for gains than for losses;

[1] Throughout, when I refer to portfolio performance, I mean the proportion of stocks in gain in the portfolio.

Ben-David and Hirshleifer, 2012), the countercyclical movement of the disposition effect with the stock market (Bernard et al., 2021), and also the well-known excess volatility of returns and equity premium puzzles.

My empirical analysis exploits two comprehensive datasets. The first dataset is provided by Barclays Stockbroking, one of the largest execution-only discount brokerages operating in the United Kingdom. I use individual investor account data from a four-year period. The data contains detailed records of positions held by investors, as well as their daily trading and login activity on their accounts. These features allow me to calculate returns on purchased stocks at a daily frequency for both selling days and login days. I use these returns to rank stocks. The second dataset is the same as in Barber and Odean (2000), Hartzmark (2015), and Strahilevitz et al. (2011). The dataset comes from a large discount brokerage (hereafter referred to as the LDB dataset) and includes daily transactions and monthly positions from January 1991 to November 1996. As with the first dataset, I calculate returns on purchased stocks and use them to rank stocks (albeit only for selling days). The LDB dataset is one of the most widely used individual investor datasets in the literature and so it eases the comparison of my rank effect estimates with other documented patterns in investor trading behaviour.

To provide compelling evidence for how rank preferences fluctuate in response to changes in the portfolio performance, I start by revising and extending the most common approach used to quantify rank effects, which computes average sales for each rank category, polling sales data of portfolios of different sizes at the account $\times$ stock $\times$ day level (for more details, see Hartzmark, 2015). Despite the initial focus on the method, it is important to emphasize that the argument developed here should not be understood as suggesting that the original rank effect estimates are irrelevant or do not matter. Part of the point of this paper is to highlight some methodological issues that have received little attention thus far and offer some methodological suggestions for consideration.

Under the standard approach, rank categories are defined based on how far they are from the best and worst positions in the portfolio, i.e., best (worst) stock, second-best (worst) stock, third-best (worst), etc. Then, there are as many rank categories as there are stocks in the portfolio. I note two obstacles with this approach. First, although we obverse heterogeneity in

the number of stocks individuals hold in their portfolios, in most trading days investors sell only a few stocks (only one stock in over 75% of trading days in the underlying data). This implies that the probability of a sale decreases with the portfolio size and that rank positions are endogenous to the number of stocks in the portfolio. In other words, by combining portfolios of different sizes, rank effect estimates are subject to downward bias at the middle positions.[2] This mechanical confound has not been fully recognized in the literature. Moreover, because the mechanics behind it are not self-evident, earlier work was not able to distinguish between authentic and mechanical rank effects.[3]

Second, I demonstrate, via simulations, that the resulting rank effect estimates are uninformative about how prevalent rank effects are among investors and among trading days. In particular, by being unable to determine the prevalence of rank effects, the approach has ignored the possibility that a non-negligible number of investors would display trading choices consistent with rank extremeness aversion. Extremeness aversion is among the most robust behavioural phenomena in choice research. It has been found robust in the study of product positioning and branding (Kivetz et al., 2004; Lehmann and Pan, 1994; Simonson and Tversky, 1992), the development of public policies (to reduce the consumption of soft drinks for instance, Sharpe et al., 2008), and even in low-level tasks, such us the judgment of the area of a rectangle (Trueblood et al., 2013).[4]

Thus, the first part of this paper offers a new and complementary approach for assessing rank effects. I test rank preferences by computing the proportion of selling days in which

[2] To see this, note that if investors reduce their position in one randomly selected stock from their portfolio every trading day, stocks in categories further from the best and the worst positions (that is, close to the middle position, e.g., the fifteenth best (worst) in a portfolio with 30 stocks) would have intrinsic low selling probabilities in the pooled data that combines portfolios of different sizes.

[3] For instance, the most comprehensive work on rank effects, provided by Hartzmark (2015), makes no mention of how this mechanical confound could bias conclusions drawn from the inspection of raw patterns in the data and analyses of main regressions. Even when this confound is partially offset by adding dummy variables for account × day fixed effects, a more exhaustive treatment demands the study of trading patterns for different sub-samples of the data split by the number of stocks held (i.e., allowing rank effects and coefficients from other control variables to vary across sub-samples). Moreover, a complete treatment also demands the study of the prevalence of the rank effect among investors and trading days, while accounting for this mechanical bias. The first part of this paper offers a new approach aiming to achieve these goals.

[4] Although researchers might be tempted to restrict the analysis to portfolios of the same size—which is to some extent equivalent to controlling for the number of stocks in the regression analysis or, alternatively, to adding account × day fixed effects—in order to correct the first problem, this strategy doesn't deal with the second problem described here. That is, rank effect estimates remain uninformative on how frequently people display preferences for extreme returns.

only the stocks belonging to a particular rank category were sold. I classify the stocks under three categories, the two best positions, the two worst positions, and the middle positions, where the latter category contains any stock in between. However, the patterns I observe are robust to using a broader rank categorization that divides the stocks into terciles based on their performance.[5]

In the raw Barclays data, I observe that on most trading days investors sell either their best positions or their middle positions (39% and 30% of days, respectively), and only on a small fraction of days (17%) investors realize their worst positions.[6] Although small in the aggregate sample, the preference for selling the worst-ranked stocks almost doubles in the subset of days in which investors held portfolios with a large proportion of stocks in gain, which provides initial evidence for the asymmetric rank effects of primary concern in this paper.

While the analysis described above allows us to get a good sense of the prevalence of the rank preferences in the data, the next part of the paper focuses on testing the moderating role of the portfolio performance on rank effects. To rule out possible omitted variable concerns related to stock-specific factors correlated with the rank positions, such as volatility, skewness or dividend announcements, it is necessary to analyze the data at the account × stock × day level to allow the inclusion of relevant control variables. Nonetheless, I exclude from the analysis all middle positions in order to avoid the confounds introduced by studying portfolios of different sizes that bias downwards preferences for middle positions.[7] This structure of the data allows for a clean identification of rank effects by comparing the trading behaviour across investors who have held the same stock on the same day, but who differed in the composition of their remaining portfolio. My baseline regression model includes dummy variables to indicate rank positions and interaction terms with the portfolio performance.

[5] While one could compute selling preferences for each precise ordinal rank (as it is done by the conventional approach described earlier), doing so assumes that investors can recognize the precise ordinal position of each stock in their portfolio. However, it is unlikely that investors can do so effectively. A large body of studies in perception research shows that the number of separate categories that individuals can reliably identify without error along a single physical dimension is often very small (about 7 ± 2 according to Miller, 1956).

[6] About the same percentages are found in the LDB dataset. These percentages do not necessarily add to 100% because they only include days in which the investor sold stocks exclusively from one of the three rank categories, i.e., observations from an investor selling a position from the top rank category and another from the middle-rank category are not included in the computation of the percentages for these two rank categories.

[7] This exclusion does not represent a concern since my goal now is no longer to investigate the prevalence of rank preferences across all rank categories but to analyse how preferences for the best and worst positions fluctuate within accounts.

In a series of tests, I show that the observed asymmetric rank effects are robust to a wide range of checks. First, they are not driven by the disposition effect (i.e., the preference for selling winner stocks over loser stocks or sign realization preferences). Second, they are robust to controlling for magnitude realization preferences (i.e., magnitude of stocks' returns). Third, the results are not driven by unobserved (time-invariant) individual differences, such as innate ability or investors' sophistication. Fourth, by analysing different splits of the data, I show that the results are not specific to particular demographic groups or portfolio characteristics.

As part of further robustness tests, I also offer a more detailed account of confounds arising from the disposition effect. In a recent study, An et al. (2019) contrast the disposition effect for paper gain and paper loss portfolios. The authors' main finding is that the disposition effect diminishes in paper gain portfolios. I present a series of econometric exercises that provide compelling evidence for independent effects for these two phenomena.

Collectively, to the extent that the documented asymmetric rank effects are pervasive in two different datasets, these results provide much support for the interpretation of the rank effect as a fundamental component of investor behaviour. These results demonstrate that once we consider the influence of the portfolio performance on the rank effect, we are able to elucidate large variations in trading behavior across assets.

The remaining question is what is the mechanism by which the portfolio performance moderates rank effects? To shed light on this, I start by examining three rational-based explanations. I test whether the results are driven by portfolio rebalancing motives or by tax-motivated selling. I also test whether beliefs in mean-reverting stock returns could account for the observed patterns. All these alternatives are ruled out by additional checks.

Next, I discuss two non-exclusive behavioural explanations. First, I consider the possibility that portfolio value movements induce (hedonic) utility at the moment investors observe them[8], and that investors attending to underperforming portfolios become more risk averse and fearful of further losses. This increase risk aversion, added to the assumption that investors pay more attention to extreme-ranked stocks, will motivate the sale of their best positions. This narrative is consistent with findings from Thaler and Johnson (1990), who show that a loss is less painful

[8] Therefore, investors derive utility from both the (paper) gains in their portfolio as well as and the realized gains from stock liquidations, evaluating these two in two different "choice brackets".

to people when it comes after a substantial prior gain (the house money effect). Conversely, prior losses make people more risk-averse to gambles that risk additional losses.

The work of Imas (2016) on how prior outcomes affect risk attitudes is instructive. When evaluating prospects, if the decision-maker can integrate his prior losses with the potential future payoffs (i.e., using the same choice bracket), then gambles that allow him to erase prior losses become more attractive. However, if he cannot integrate his prior losses with the potential future payoffs, he will become more apprehensive of further losses. The latter case occurs when the decision-maker has already internalized the adverse outcomes from prior losses (i.e., he has already suffered the pain of admitting the losses), and by doing so he has closed the associated choice bracket.

The second mechanism I consider is the possibility that investors take actions to self-regulate their mood. Isen and colleagues show that people in whom positive affect have been induced are reluctant to gamble, sometimes avoiding significant large stakes and even when there is increased optimism about winning (e.g., Isen and Patrick, 1983; Isen et al., 1988; Isen, 2000). Hence, if individuals often implement a range of strategies to regulate their mood, trading could be one of these self-regulating strategies, i.e., selling a stock at a gain could offset the mood effects induced by observing portfolios in loss. However, the finding that investors are willing to sell their best stocks, even when these stocks are in loss since purchase, casts doubt on this interpretation of the results.

The paper also devotes a section to the study of the role of salience in producing the reported asymmetric rank effects. An intuitive explanation for the rank effect is that extreme positions are more salient (or more attention grabbing) in the investors' portfolios. To establish whether salience itself (orthogonal to any economic explanation) can account for this phenomenon, Hartzmark (2015) tested the effects of an alternative rank order based on the alphabetical order of companies' names—as stocks are often displayed in this order online or in brokerage statements. He found that the first and last positions by alphabetical order are more likely to be sold. While salience constitutes an important determinant of the rank effect, the mechanisms described above are agnostic as to whether portfolio fluctuations will increase trading in stocks with a salient characteristic unrelated to what the investors' choice

brackets are balancing off (i.e., unrelated to stocks' gains and losses). To test for this possibility, I examine the interaction effect of the portfolio performance and the referred alphabetical rank effect on stock sales. Regression estimates reveal a null effect for this interaction. Unexpectedly, these estimates also reveal null effects for the (independent) alphabetical rank positions, a result that is confirmed by further robustness checks. The paper features a discussion on the interpretation of these findings.

The last part of the paper examines the implications of the primary mechanism discussed above on a particular related phenomenon: the asymmetric V-shaped selling propensity in response to unrealized profits (i.e., the observation that the investors' selling probability increases as the magnitude of gains and losses increases, with a steeper slope for gains than for losses, documented by Barber and Odean, 2013, Ben-David and Hirshleifer, 2012, and Seru et al., 2010). Elucidation of this phenomenon is important because, as findings from An and Argyle (2020) point out, this trading behaviour can impact equilibrium price dynamics and generate subsequent return predictability in the cross-section. The most generally accepted explanation, developed by Ben-David and Hirshleifer (2012), contends that this trading pattern may arise from speculative trades who revise their beliefs about the future performance of their stocks when large price movements occur. This paper proposes a complementary but distinct view of this phenomenon, namely, that it stems in part from changing risk attitudes when the portfolio performance fluctuates over time (in accordance with the main behavioural mechanism described above). It is intuitive to expect that preferences for extreme-ranked stocks and preferences for extreme returns should generally move in the same direction. These expectations are verified in the data.

In addition to motivating a new explanation for the rank effect observed in the cross section and providing insight on the V-shaped investors' selling propensity, the primary results of this paper can also shed light on two key puzzling features of asset pricing: the excess volatility of returns and the equity premium puzzle. Changes in risk aversion driven by acknowledging shifts in the portfolio value might explain high volatility in returns, which could lead to persistent losses, making our loss-averse investors require a high equity premium to hold stocks.[9] My

[9] Barberis et al. (2001) offer a more formal way of thinking about these puzzles in a framework that assumes that investors derive utility not only from consumption levels but also from changes in their financial wealth.

results are also consistent with the observed countercyclical fluctuations of the disposition effect with the stock market (Bernard et al., 2021). Part of these fluctuations may be owed to changes in risk preferences if boom periods correlate with a large proportion of stocks in gain in the investors' portfolios, while bust periods correlate with a large proportion of stocks in loss.

This paper contributes to several strands of the literature. It extends earlier research examining the role of prior losses on subsequent risk-taking behaviour (Andrade and Iyer, 2009; Imas, 2016; Langer and Weber, 2008; Shiv et al., 2005; Weber and Zuchel, 2005). In particular, my results speak directly to the work of Imas (2016) who draw a distinction in how individuals respond to realized (versus paper) losses. As discussed earlier, he demonstrates with experimental evidence that individuals take on less risk after a realized loss because realized losses are evaluated in a different choice bracket. In this paper, I argue that portfolio losses could be treated as realized losses in Imas' framework, provided that they cause a drop in utility when investors attend to them.

This paper is also related to the strand of work that study the role of context effects in behaviour. In particular, the behavioural and marketing science literature has suggested that people are averse to making extreme choices when facing uncertainty (e.g., Simonson, 1989; Simonson and Tversky, 1992). I expand this line of work by investigating rank extremeness aversion in trading behaviour. Although large, the literature on extremeness aversion has paid little attention to the study of investors' decision making.

In the broader literature, the paper is also related to growing research on behavioural biases exhibited by individual investors. Investors often display pervasive biases such as the disposition effect (Odean, 1998; Shefrin and Statman, 1985), narrow framing (Barberis et al., 2006; Kumar and Lim, 2008), and overconfidence (Barber and Odean, 2001). Investors also appear to employ basic heuristics to limit the set of stocks between which to choose, trading often based on attention grabbing characteristics (Bordalo et al., 2012; Hartzmark, 2015; Itzkowitz et al., 2016; Jacobs and Hillert, 2016). Moreover, while there is much evidence suggesting that trading is focused on attention-grabbing stocks, such as stocks with extreme returns,[10] much

[10] For examples, see An and Argyle (2020); Barber et al. (2005); Barber and Odean (2008); Frydman and Wang (2020); Hartzmark (2015); Meng and Weng (2018).

less is currently known about when investors shift their preferences toward other asset types. Here, I demonstrate that fluctuations in the portfolio performance can elucidate part of these shifts in investors' preferences.

The paper proceeds as follows: Section 2 describes the data used in the study. Section 3 discusses the standard measures researchers have proposed for the study of rank effects. Section 4 presents the empirical analysis aimed to quantify the prevalence of rank effects in the data. Section 5 focuses on testing the moderating role of the portfolio performance and is followed by additional robustness and sensitivity tests. Section 6 discusses the main findings and concludes.

2 Data

This paper makes use of two comprehensive datasets on retail investors. The first dataset is provided by Barclays Stockbroking, an execution-online brokerage service operating in the United Kingdom. The data include daily trading activity of new accounts that open after the beginning of April 2012, which I follow until March 2016. The analysis focuses solely on new accounts because to be able to rank stocks based on their performance, I need to calculate returns since purchase on all stocks held within each account. For the computation of returns, I matched each security identifier in the data against SEDOL codes in Datastream to find the market prices on the day.[11] The sample excludes investor × stocks for which the purchase price is unknown because either their security codes could not be linked to Datastream codes, or because their positions were transferred into the account during the sample period (from a different brokerage service provider). The sample also excludes days on which the investor held fewer than five stocks, following Hartzmark (2015). Stocks are not included on the day that their position is opened. The final baseline sample includes 4100 accounts. A breakdown of the steps in sample selection and data exclusions is provided in Table A1.

The main analyses use days when the investor made at least one sale (Sell-Days). This sample restriction is standard in the literature (beginning with Odean, 1998) given that in the

[11] When investors purchased additional shares of a stock, I use the weighted-average purchase price as the purchase price for the computation of returns.

remaining days it is not certain that investors were aware of all prices and returns on their stocks (i.e., it is not possible to distinguish whether the absence of a sale is the result of a deliberate choice or due to inattention). However, besides trading activity, the data also includes records of investors' login activity (a daily-level dummy variable for whether the investor made a login to the online trading platform). Given this feature of the data, I am able to replicate the main analyses using the extended sample of Login-Days (which incorporates the Sell-Days sample). On these days, investors accessed their portfolio, gathered information on their stocks' prices and returns, and could potentially make a trade. Therefore, the absence of a transaction can be considered part of a deliberative choice.

Table A2 shows summary statistics for the baseline sample. The majority of account holders are male (approximately 85%). Their average age is 50 years, and they have held their accounts with Barclays for roughly two years on average. The average portfolio value is approximately £60,000; however, the median investor holds a much smaller portfolio of about £14,000. Portfolios contain eight stocks on average in the baseline sample but note that this sample excludes account × days with fewer than five stocks. Besides holding a few stocks, only a small proportion of the portfolio size (by value) is invested in mutual funds (7.8%). This profile of investors is consistent with the characteristics described in a broad set of studies analysing retail investors.

Table A2 also presents statistics for login and transaction activity. Account holders log in to their accounts much more frequently than they trade. They log in on average once every four days, but make a transaction only once every fifteen market open days (i.e., approximately once every three weeks). Again, this much more frequent login activity is reminiscent of login patterns observed among retail investors in the United States (see Sicherman et al., 2016).

The second dataset (the LDB dataset) is the same as Barber and Odean (2000), Hartzmark (2015), and Strahilevitz et al. (2011). The LDB dataset comes from a large discount brokerage and includes daily transactions and monthly positions from January 1991 to November 1996. Like with the first dataset, the analysis focuses solely on new accounts (albeit it is restricted to Sell-Days). To calculate returns on purchased stocks and use them to rank stocks, I augmented the data using daily CRSP prices and split factors because prices in the LDB dataset are not

adjusted for splits and dividends.[12] Following Odean (1998), Ben-David and Hirshleifer (2012), and Hartzmark (2015), I restricted the analyses to US common stocks, removed any account × stocks with negative commissions or that included short sale transactions. The final sample retains days on which the investor held at least five stocks and stocks are not included on the day that their position was opened. The final baseline sample consists of 7083 accounts. A detailed breakdown of the steps in sample selection and data exclusions is provided in Table B1. Table B2 shows summary statistics for this baseline sample. The average portfolio value is approximately £57,000; however, the median investor holds a much smaller portfolio of about £27,000. Portfolios contain eight stocks on average in the baseline sample but, again, note that this sample excludes account × days with fewer than five stocks.

At this point, it is important to stress that while for comparability with the original rank effect estimates, both datasets are restricted to portfolios containing at least five stocks, in reality, retail investors are much more under-diversified. In both datasets, the median investor holds only three stocks in their portfolios before narrowing the samples (with an upper interquartile range of six stocks).[13] Thus, analyses of the data may be arguably constrained to less conventional investors who might desire to diversify their asset allocation and rebalance over time.[14]

3 Difficulties in the Estimation of Rank Effects

This section describes the standard framework used in the asset pricing literature to test for rank effects and its major drawbacks. Rank effects are frequently tested by analysis days in which the investor made at least one sale, and then pooling the data at the account × stock × day level. Thus, each observation is a stock (j) for an investor (i) on a sell day (t). Ranks are defined based on returns from purchase within accounts. The following proportions define

[12] Returns in the Barclays dataset use the closing price of the sell day. However, for comparability with Hartzmark (2015), returns in the LDB dataset use the closing price on the day prior to the sell day. In both cases, rank effect estimates are not much different when using either the closing price of the sell day or that of the day before the sell day for the computation of returns. Figure A1 shows that returns are approximately normally distributed with mean at zero for the Barclays dataset. Figure B1 shows that returns are more positively skewed for the LDB dataset.

[13] Preferences for small portfolios are prevalent among retail investors and appear to be driven by preferences for skewness, volatility, and low prices (Kumar, 2009; Mitton and Vorkink, 2007).

[14] In Section 5, I study whether the findings of the paper arise from investors' desire to rebalance their portfolios .

rank preferences.

$$
\begin{aligned}
Best &= \frac{\#Best\ Sold}{\#Best\ Sold + \#Best\ Not\ Sold} \\
2nd\ Best &= \frac{\#2nd\ Best\ Sold}{\#2nd\ Best\ Sold + \#2nd\ Best\ Not\ Sold} \\
Middle &= \frac{\#Middle\ Sold}{\#Middle\ Sold + \#Middle\ Not\ Sold} \\
2nd\ Worst &= \frac{\#2nd\ Worst\ Sold}{\#2nd\ Worst\ Sold + \#Worst\ Not\ Sold} \\
Worst &= \frac{\#Worst\ Sold}{\#Worst\ Sold + \#Worst\ Not\ Sold}
\end{aligned}
$$

In the first proportion, *#Best Sold* is the number of best-ranked stocks on a sell day that had their positions decreased, and *#Best Not Sold* is the number of best-ranked stocks for which the number of shares stayed the same or increased. The remaining proportions are computed in the same fashion. Note that middle stocks incorporate stocks not ranked in the top or bottom two positions. These measures, proposed by Hartzmark (2015), are analogous to the proportion of realized gains (losses) used by Odean (1998).

The rank effect can be seen by examining the bottom part of Table 1. Best–Middle is the difference between the best and middle proportions described above (with standard errors clustered by date and account underneath). On selling days, a best-ranked stock appears to be 25.9% more likely to be sold than a middle-ranked stock, and a worst-ranked stock appears to be 6.9% more likely to be sold than a middle-ranked one. The results using login days in Column 1 display parallel patterns, i.e., a stronger preference for extreme ranks than for middle ranks.

A visual representation of rank effects can be seen in Figure 1, where this time the proportions are computed for the best four and the worst four ranked stocks, again, polling all observations in the data. We observe a clear "U" shape pattern, with some larger preferences for higher ranked stocks. The overall patterns we observe in Table 1 and Figure 1 replicate the initial set of results presented by Hartzmark (2015), but using a different dataset. Table B3 and Figure B2 in the Appendix replicate these patterns in the LDB dataset. The consistency of these results might tempt us to conclude that on most trading days investors expose rank

preferences for both the best and the worst ranked stocks. However appealing these patterns may initially be, there are concerns to address before we connect rank preferences to trading patterns. Next, I demonstrate that rank effects are artificially inflated when observations from different portfolio sizes are pooled together for the analysis. Leaving aside this concern, there is a major difficulty with the interpretation of rank effect estimates: rank effect estimates fail to provide information on the prevalence of rank effects; that is, on how often people will display preferences for extreme ranks.

3.1 Bias Introduced by Ignoring Heterogeneity in Portfolio Sizes

First, consider that in the data people sell often only one stock even when they hold large portfolios (as illustrated by Figure 2 for the Barclays dataset and Figure B3 for the LDB dataset). This behaviour implies that by mixing portfolios of different sizes, but with no rank preferences, it is possible to obtain an (artificial) rank effect. Observe Figure 3 where I simulate 1000 trading days for three investors (in panels (a), (b), and (c)) who hold portfolios of various sizes. Every day, investors reduce their position in one randomly selected stock from their portfolio. Panel (d) aggregates all trading days from these three investors. Panel (d) reveals a smooth "U" shape, even when, by construction, these investors hold no preferences over stocks' ranks.

Second, even if we restrict the analysis to stocks belonging to portfolios of the same size (which can be achieved, to some extent, by adding account $\times$ day fixed effects on a regression framework, for instance), the magnitude of the rank effect estimates is not informative to the extent on which people display rank effects, i.e., rank estimates do not inform on the prevalence of rank effects across trading days or across investors. This point is particularly important because without a proper sense of the scale and magnitude of rank effects, we are unable to determine how pervasive these effects are in the data.

To illustrate this point, see the top panel of Figure 4 where I simulate data for three types of investors who hold each ten stocks. The first type of investors prefers to sell low-ranked stocks; the second type is averse to extreme ranks but has no particular preference for any stock in middle positions; and the third type prefers to sell high-ranked stocks. Subpanel (d) aggregates the trading days of these three types of investors in equal proportions.

Now observe the bottom panel of Figure 4, where I repeat the same exercise, but this time investors hold portfolios of 20 stocks. Subpanel (d), again, aggregates trading days from these investors, but now investors holding aversion to extreme ranks compose 50% of the total sample. Results from the aggregate samples are striking. First, both subpanels (d) reflect a "U" shape, despite the fact that no single investor in these simulated samples holds simultaneous preferences for extreme ranks (i.e., best and worst stocks). Thus, a "U" shape can arise not necessarily from individuals preferring liquidating both low-ranked and high-ranked stocks together, but from individuals holding different and opposed rank preferences—or from investors fluctuating their rank preferences across days if we treat panels (a), (b), and (c) as "day" types instead of "investor" types. Second, the aggregated samples in these two panels appear identical even when a much larger proportion of investors is averse to extreme ranks in the second panel. It is trivial to generate examples in which a "U" shape emerges despite the addition of a much larger proportion of extreme averse investors.

3.2 Neglecting Potential Rank Extremeness Aversion

Moving now to consider potential rank extremeness aversion, using the choice share proportions of the middle option in a choice set is often considered as the most direct measure to evaluate the tendency to avoid extremes, as documented in the extensive literature on context effects (e.g., Neumann et al., 2016; Simonson and Nowlis, 2000). Following this line of work, I proxy rank extremeness aversion by the observed preferences for middle stocks.

As clearly seen in Figure 4, aversion to extreme ranks is more difficult to detect in portfolios that hold many stocks. Again, in the bottom panel, in subpanel (b), 50% of the aggregate sample has aversion to extremes ranks, but this aversion is not obvious by plotting selling probabilities for each rank in the aggregate sample. Although subpanel (b), displaying preferences for middle stocks, is designed to illustrate the methodological constraints of the standard framework, it is not necessarily rare. Because of salience, an investor can easily detect which are their best and worst performing stocks but could hardly identify the precise rank position of their middle stocks. As a consequence, the probability of selling middle stocks, assuming aversion to extreme ranks, will tend to be more uniformly distributed across middle stocks, particularly

when the portfolio size is large.

3.3 How Do Investors Frame Rank Categories?

The estimation of rank effects raises the question of which (rank) groups make more sense to compare to test for rank preferences? Going back to Table 1, the contrast between Best vs. Middle ranks in the bottom part of the table compares rank preferences under the assumption that investors can distinguish the precise rank of every stock and hold a preference for each of these precise ranks. Notice that due to the structure of the data (in which each observation represents an account × stock × day), the row displaying the proportion of stocks sold in the middle ranks is, in fact, displaying the average selling probability across $N - 4$ groups, where N is the number of stocks in the portfolio, and each group corresponds to one specific rank.

To see this, let us ignore for the moment the problem brought by pooling together portfolios of different sizes and let us assume that all portfolios hold N stocks across all trading days. Then, suppose every day, across T trading days, an investor (partially) sells only one stock in the middle positions. In that case, the proportion corresponding to the middle positions, which indicates the preference for middle stocks, will be equal to $\frac{T}{(N-4)T}$. This figure could be negligible as N grows even though the investor has continuously sold only stocks in the middle positions. In other words, Table 1 displays rank preferences under the assumption that investors are classifying N stocks in N rank groups. But when investors, instead of classifying N stocks in N groups, classify them in just a few groups, then the analysis of rank preferences should consider a different structure, one in which the preference for middle positions is not (mechanically) penalized by holding a large number of stocks. This constraint is not the result of mixing portfolios of different sizes, and so it cannot be addressed by adding controls for the number of stocks in a regression framework.

The quantification of preferences for certain alternatives requires individuals to be able to distinguish these alternatives. In the same fashion, the quantification of rank preferences requires individuals to be able to recognize rank categories. How do investors frame rank categories? A body of research shows that individuals have great difficulty identifying the ordinal position of a stimulus from a set of stimuli that varies along a single psychological

continuum. In most absolute identification experiments, performance (e.g., percentage of correct responses) at the ends of the stimuli's range is better than performance in the middle of the range. Errors in accuracy in the middle of the range are even more pronounced when the number of items to identify increases beyond five (Kent and Lamberts, 2005; Stewart et al., 2005).[15]

This phenomenon is not particular to a certain stimulus dimension. It has been observed across a wide range of dimensions such as the magnitude of lengths of line segments (e.g., Lacouture, 1997), the weight of containers (e.g., Neath et al., 2006), the duration of tones (e.g., Brown et al., 2005), and even judgments of odor intensity (e.g., Engen and Pfaffmann, 1959).[16] The combination of these findings suggests that there are fundamental limitations to how well individuals can discriminate alternatives from a set of items that vary on a single dimension (e.g, stocks' performance, for the purposes of this paper).

When investors are unable to classify N stocks in N rank groups, the analysis of the data at the account $\times$ stock $\times$ day level is not only uninformative on the prevalence of rank preferences across investors (and across trading days), but it also complicates any test for rank extremeness aversion.

In order to address these concerns, I proceed as follows. First, I examine separately portfolios of small size, for which investors are more likely to be able to differentiate stocks' ranks. Second, using all data, I propose a new framework for a more adequate estimation of the prevalence of rank effects across investors and potential rank extremeness aversion: I compute rank preferences using a collapsed version of the data, in which observations are at the account $\times$ day level.

3.4 Estimating Rank Effects in Small Portfolio Sizes

Because preferences for middle positions are obscured when investors hold large portfolios, to distinguish them, I first explore the probability to make a sale when investors hold only a

[15] This phenomenon is known as the bow effect, since a distinctive bow is observed when accuracy is plotted as a function of the ordinal rank of the stimulus. For a review of serial position effects in memory and absolute identification, see Brown et al. (2007).

[16] Similar effects are also observed for the analysis of reaction times, with shorter reaction times toward the ends of the stimulus range where accuracy is better (e.g., Kent and Lamberts, 2005; Lacouture and Marley, 1995).

limited number of stocks (three to six stocks). A ubiquitous experimental finding in perception research is that the number of separate categories that individuals can reliably identify without error along a single physical dimension is very small (about 7 ± 2 according to Miller, 1956). On the basis of these studies, I narrow down the set of portfolios to portfolios of between three to six stocks.

Only for this first set of analyses, I include portfolios with fewer than five stocks. The remaining of the paper, however, uses portfolios with five or more stocks, as described in Section 2. By adding accounts with three and four stocks to the main samples, we are expanding the Barclays sample by 2,529 accounts and the LDB sample by 5,870 accounts.

Figure 5 shows selling probabilities by portfolio size in the Barclays sample. For each portfolio size, I rank preferences are computed at the account × stock × day level. Column 1 suggests that the preference for the worst stocks might be smaller than originally observed in Table 1 once we account for the portfolio size and include the same number of observations for each rank category. Comparing the height of the middle bars with that of the end bars, potential aversion to extreme ranks doesn't appear negligible in this preliminary analysis of small portfolios, with some middle ranks displaying larger selling probabilities than the worst ranks.

In Figure 5, I also provide an initial test of the moderating effect of the portfolio performance on rank preferences. In the figure, and throughout the paper, portfolio performance is proxied by the proportion of stocks in gain in the portfolio. Columns 2 and 3 split the data by the portfolio composition of winner and loser stocks. Column 2, which includes portfolios composed mainly of loser stocks, highlights a preference for selling the best performing stocks. This preference is much less pronounced in Column 3, which consists of the remaining portfolios. Contrasting Columns 2 and 3, we observe that the small probability of realizing the worst stocks raises marginally once the portfolios are composed of more winner stocks. These distinct trading patterns in Columns 2 and 3 are also found in the LDB sample (Figure B4).[17] This evidence serves as the starting point of the central idea in this paper: rank effects depend crucially on the portfolio performance.

[17] In Figure B5, we can note that the "U" shape emerges as the number of stocks increases, which suggest that the rank effect is a feature of large portfolios.

In Table A3 and Table B4, I repeat the initial comparison of the first and the middle stocks performed earlier but when all ranked groups include the same number of observations (i.e., using only 5-Stocks portfolios). We observe that the preference for the worst-ranked stocks decreases substantially in comparison to Table 1.

Whereas these results generally point to smaller rank effects than those displayed in Table 1, they are restricted to small-size portfolios. In the next session, I propose and new methodological framework that enables me to examine portfolios of much larger size without the constraints described above.

4 Prevalence of Rank Effects

How should we analyze portfolios of a much larger size? To provide rank effect estimates that are informative on the prevalence of rank preferences, I move from an analysis of selling probabilities at the account× stock × day level to an analysis at account× day level. This data structure is coherent with the finding that investors often sell only one stock independently of their portfolio size. This data structure also has the advantage of facilitating the detection of potential aversion to extreme ranks.

For the reasons described above (i.e., the difficulties with how well individuals can discriminate ordinal positions), I define three rank categories: *Best Rank*, composed by any stock from the top two; *Worst Rank*, by any stock from the bottom two positions; and *Middle Rank*, by positions in between. Even though these categories appear reminiscent of those of Table 1, there is a substantial difference in how they are computed. Table 1 assumes that investors classify N stocks in N rank groups. Middle stocks in Table 1 contain the average preference over $N - 4$ rank groups. Here, however, I assume that investors classify N stocks into three rank groups. Thus, middle stocks correspond to only one rank group.

Panel A of Table 2 shows rank preference using Barclays data at the account × day level. The sample includes days in which the investor made at least one sale. The first column shows the proportion of selling days in which the investor sold any stock from the top two positions (*Any Best Rank*), the bottom two positions (*Any Worst Rank*), or positions in between (*Any Middle Rank*). Proportions are not mutually exclusive, i.e., observations from an investor

selling a position from the top rank and another from the middle rank will contribute to the computation of proportions for these two rank categories. Columns 2 to 5 split the sample by the proportion of stocks in gain in the portfolio. Column 2 includes days in which over 75% of stocks in the portfolio were in loss; likewise, Column 5, days in which over 75% of stocks were in gain. Panel B repeats the same exercise, but proportions are computed including days in which the investor sold stocks in only one rank category, i.e., observations from an investor selling a position from the top rank category and another from the middle rank category will not be included in the computation of the proportions for these two rank categories.

Raw patterns from Column 1 reveal that on most trading days investors sell either their best positions or their middle positions (39% and 30% of days, respectively), and only on a small fraction of days (17% of the days), investors prefer to realize exclusively their worst positions.[18] Contrasting the size of these observed preferences with those obtained using data at the account × stock × day level (in Table 1), underlines the downward bias at the middle positions introduced by the conventional analysis, under which we could have inappropriately concluded that investors overwhelmingly prefer to realize both their best and worst stocks together.

Preference for middle stocks from Panel B reveals that potential rank extremeness aversion is not trivial, with about 30% of account × days corresponding to sales of stocks from the middle category. A remarkable feature of Table 2, across both panels, is how large is the drop in the preference for realizing the best-ranked stocks when the portfolio composition moves from 0%-25% stocks in gain to 75%-100% stocks in gain (a drop of 40% in the proportion of sell days in which investors sold any stocks from the top two positions). This change in the preference for the best stocks is accompanied by a marginal increase in the preference for realizing stocks from the bottom two positions. Although small in the aggregate sample, the preference for the worst-ranked stocks almost doubles in the subset of days in which investors hold portfolios with a large proportion of stocks in gain.

To facilitate the interpretation of the data, Panel A of Figure 6 plots the rank preferences

[18] These percentages do not necessarily add to 100% because they correspond to days in which the investor sold stocks exclusively from one of the three rank categories, i.e., observations from an investor selling a position from the Only-Best rank category and another from the Middle rank category will not be included in the computation of the percentages for these two rank categories.

for the case of mutually exclusive rank categories. We observe a moderate trade-off between the extreme rank categories, while preferences for middle stocks change little. One may question whether these patterns are specific to the particular categorization used. In Panel B, I show the selling proportions under an alternative definition of the *Best* (*Worst*) stocks. Instead of including the top (bottom) two positions, the category consists of positions in the top (bottom) tercile of the rank distribution. There are no meaningful differences between the two panels despite the different categorizations used. Table B8 and Figure B6 display comparable results for the LDB dataset.

Combining these sets of results with those from the analysis of small portfolios, the foremost finding is that rank preferences are not stable across trading days. Instead, they fluctuate, with variations being determined by the portfolio performance. Additionally, pure preferences for middle stocks (that can reflect potential rank extremeness aversion) are not negligible, as we could have inferred from Figure 1 or Table 1. On the contrary, in the aggregate data, stocks in the middle positions are much more frequently traded than stocks in the lowest-ranked positions.

A valid criticism of the above analyses is that patterns in Table 2 could be confounded by stock-specific factors correlated with the rank positions, such as volatility or skewness, or perhaps by unobserved investor characteristics. The second part of the paper deals with these concerns. The goal of the following analyses is no longer to study the prevalence of rank preferences across all rank categories but to analyze how preferences for the best and worst categories fluctuate within accounts.

5 Asymmetric Rank Effects

To rule out possible omitted variable concerns related to stock-specific factors correlated with the rank positions, it is unavoidable to change the structure of the data in order to allow the inclusion of an array of relevant control variables. Thus, in this section I proceed to analyse the data at the account × stock × day level but excluding all the middle positions, avoiding

the confounds introduced by combining portfolios of different sizes[19]—which bias downwards preferences for middle positions. This exclusion does not represent a concern because, as highlighted earlier, my goal is no longer to study the prevalence of rank preferences across all rank categories but to analyse how preferences for the best and worst positions vary within accounts. One attractive feature of this structure of the data is that it enables a clean identification of rank preferences (on extreme positions). It allows us to compare the trading behaviour across investors who have held the same stock on the same day, but who differed in the composition of their remaining portfolio (i.e., by controlling for stock × days fixed effects in the econometric specification). My identification, therefore, comes from stocks that share the same underlying characteristics but that belong to different portfolios.

Before turning to the econometric analysis, it is useful to illustrate raw patterns from this new structure of the data. Table A4 displays the underlying rank preferences. The last rows of the table test statistically whether the gap Best-Worst is nonzero.

Observe that Table A4 is reminiscent of Table 1 but using a balanced number of observations per portfolio. The Best-Worst gap diminishes with improvements in the portfolio performance. The Best-Worst gap is on tenth in Column 5 compared to the gap in Column 2. Here again, as expected, we find evidence of the moderating role of the portfolio performance on rank effects.

Moving on now to consider the econometric specification used to estimate rank effects.

$$\begin{aligned} Sale_{ijt} =& b_0 + \beta(Rank\ Variables_{ijt}) + \gamma(Proportion\ of\ Stocks\ in\ Gain_{ijt}) + \\ & \phi(Rank\ Variables_{ijt} \times Proportion\ of\ Stocks\ in\ Gain_{ijt}) + \epsilon_{ijt}, \end{aligned} \tag{1}$$

In Equation 1, the unit of observation is an account × stock × day. $Sale_{ijt}$ takes a value of 1 if investor i made a sale of the stock j, and is zero otherwise. $Rank\ Variables_{ijt}$ are four dummy variables indicating the ordinal positions of the stocks in the portfolio (referring to best, 2nd best, 2nd worst, and worst positions). The model also includes the interaction terms of these ordinal positions with the portfolio performance. Across a series of analyses, I add standard control variables to the main specification, such as controls for the portfolio size

[19] Under this new structure of the data, I include four observations per day, the two highest ranked stocks and the two lowest ranked stocks. Thus, for every investor, the data contains the same number of observations on each selling day.

(i.e., the number of stocks in the portfolio), for the time elapsed since purchase, and for the disposition effect (i.e., sing realization preferences). Standard errors are clustered by account × day.

In subsequent robustness analysis, I also estimate models that add i) individual fixed effects to control for individual-specific time-invariant heterogeneity in selling behavior, ii) stock × day fixed effects to control for time-varying stocks characteristics, iii) and continuous measures of returns since purchase above and below the zero threshold (i.e., controls for magnitude realization preferences). I also present additional sub-sample analyses based on different investor and portfolio characteristics; and replicate the main findings using the sample of Login-Days in Barclays data.

Finally, Appendix B also features a discussion on the interpretation of Table 5 in Hartzmark (2015)[20], which looks at rank effects on portfolios for which all positions are either at a gain or at a loss.

5.1 Main Results

Table 3 shows the coefficients from a series of regressions based on Equation 1 using Barclays data. Controls are added sequentially. The omitted rank category across columns is the worst stock. As a starting point, Column 1 shows the main specification without interactive terms. The coefficient on second-worst dummy captures the change in selling probabilities when the stock increases performance and moves from the worst position to the second-worst position. The magnitude of the second-worst and best coefficients suggests that there are significant changes in selling probabilities when stocks reach extreme positions. However, these changes are not uniform: the probability of a sale raises in 13.8pp when the stock reaches the best position (from the second-best); while the probability of a sale raises by only 3.6pp when it reaches the worst position (from the second-worst). These patterns are consistent with raw estimates from Table A4.

Column 2 adds controls for the performance of the portfolio and Column 3 adds the interaction terms. The coefficients on the interaction terms in Column 3 capture the extent to

[20] A copy of Table 5 in Hartzmark (2015) is shown inTable B6.

which the gaps between the worst stock and the other ordinal categories are moderated by the portfolio performance. We observe that the interactions are all significant at the 1% level. What stands out is the magnitude of the interaction terms. The negative coefficient on the interaction term with the best stock is 1.4 times the magnitude of the independent effect of the best stock, suggesting that rank preferences are largely reduced in well-performing portfolios. Negative signs across all interaction terms indicate that the preference for categories, relative to the worst position, decreases when the portfolio improves performance. As a result, there is a notable decrease in the gap between the worst stock and the top position, but a small increase in the gap between the worst and the second-worst stock. Similar findings are observed in the LDB dataset (Table B9).

5.2 Robustness Tests

5.2.1 Multiple Fixed Effects

The first robustness test adds account fixed effects to control for unobserved (time-invariant) account holder differences, such as innate ability or investors' sophistication. The test also adds stock × day fixed effects to control for potential stock-specific factors correlated with the rank positions, such as dividend announcements, volatility, or skewness. The volatility of stock returns, for instance, has been shown to influence stock trading decisions (Borsboom and Zeisberger, 2020). The addition of these fixed effects has the advantage of removing the influence of any public information about each stock that varies over time (such as past returns, market values, book-to-market ratios, etc.).

Results are shown in Table 4 for the Barclays dataset. The table reports estimates using the full specification reported in Table 3 (Column 3). The findings are in line with the baseline regressions described earlier. All coefficients of the interacting terms that are of main concern here show the expected negative signs. Comparable estimates are shown in Table B10 for the LDB dataset. Thus, the qualitative pattern of results, that the gap between the best stocks and the worst stocks diminishes when the portfolio exhibits a large proportion of stocks in gain, remains consistent even when controlling for unobservable stock-specific and investor-specific characteristics.

5.2.2 Controlling for Magnitude Realization Preferences

My main specification controls for sign realization preferences. However, Ben-David and Hirshleifer (2012) show that the propensity to sell as a function of returns is V-shaped, i.e., it raises as returns increase (decrease) above (below) zero. They also show that investors appear to be more responsive to positive changes in returns, with the right branch being steeper than the left branch. The second robustness test adds linear controls for returns to the econometric models. To take into account potential asymmetric effects for positive and negative returns, I augment the specification with linear controls for returns on either side of zero.[21]

Results are shown in Table 5 for the Barclays sample and in Table B11 for the LDB sample. The tables report estimates both without individual fixed effects and stock × day fixed effects, shown in Column 1, and with the addition of these effects across Columns 2-4. Here again, the pattern of estimates remains qualitatively the same as those shown in the main specifications of Table 3.

5.2.3 Investor and Portfolio Characteristics

The third robustness test augments the baseline econometric specifications with a broader set of control variables. Table 6 adds progressively controls for the portfolio value, account tenure (proxying investors sophistication or financial literacy), and investor demographics (age and gender). Results show that the interaction terms are stable across the different econometric specifications in Columns 1-7. Columns 6-7 add account fixed effects and stock × day fixed effects to the analysis. In all specifications, we see large and negative coefficients on the interaction effect for the best positions in the portfolio, consistent with the main results.

5.2.4 Sensitivity Tests

The fourth robustness test investigates the sensitivity of my main results across different sub-samples defined based on investor characteristics and portfolio characteristics. By allowing the coefficients on all variables to vary across subsamples, this approach eases the identification of whether the interaction effects of the portfolio performance are larger for certain types of

[21] Returns are winsorized at the 1% and 99% levels to remove the effect of outliers.

investors or portfolios. Results are shown in Table 7, with subsamples split at the median of the characteristic under study. First, I investigate the sensitivity of my main results to investors' demographic differences. The literature often highlights gender and age differences in trading behavior (Barber and Odean, 2001; Choi et al., 2002; Dorn and Huberman, 2005). However, the coefficients on the interaction terms are rather similar in the gender and age sub-samples—although the estimates reveal slightly smaller coefficients on the interaction terms for the best position for males and younger investors, baseline selling probabilities, given by the intercepts, are also slightly smaller for these groups, suggesting no meaningful relative differences in rank preferences.

Second, I explore the sensitivity of my main results to investor sophistication, proxied here by the number of years for which the investor has held the trading account with Barclays Stockbroking, the portfolio value, and the number of stocks held in the portfolio (which are restricted to a minimum of five, as described in the data section). Previous studies suggest that behavioural biases (e.g., the disposition effect) decline with trading experience and investor's wealth (Feng and Seasholes, 2005; Nicolosi et al., 2009; Seru et al., 2010). Results reveal large coefficients on the interaction terms for the best position for above-median trading experience, above-median portfolios, and above-median number of stocks held. These patterns might indicate that the moderating role of the portfolio performance is more prominent when investors hold sizable portfolios.

Moving on now to consider the effect of market conditions on my results, the next set of splits in Table 7 explore whether my results hold on both days following market upturns and days following market downturns. Estimates from subsamples that split the data based on changes in the Financial Times Stock Exchange 100 Index show qualitatively similar results across subsamples.

The last rows of Table 7 also indicate that similar qualitative patterns are observed in the subsets that divide the data by time elapsed since purchase. Together, the analysis of different splits of the data confirms that my main findings are not specific to particular demographic groups, portfolio characteristics, and marked conditions. The economic magnitude of the moderating role of the portfolio performance is substantial across subsamples, as the coefficients

on the interaction terms are all larger in magnitude than the independent coefficients on the rank positions.

5.2.5 Login-Days Analysis

The earlier analyses use Sell-Days samples. Research on retail investors is typically constrained to the study of days in which the investor made at least one sale because in the remaining days it is not possible to determine whether the absence of sales is the result of deliberate choices or due to inattention. However, as described early in the paper, the Barclays dataset also includes records of investors' login activity. Examining the Login-Days sample increases the power of the statistical tests and allows for a cleaner interpretation of the results as trading activity is usually occasional among investors, but login activity is generally regular—recall that, on average, investors make transaction approximately once every three weeks, but they log in about once every four days.

First, I show unconditional trading patterns in Table A5. The first column includes all portfolios, and Columns 2 to 5 split the sample by the proportion of stocks in gain in the portfolio. We observe a large drop in the preference for realizing the best-ranked stocks when the portfolio composition moves from 0%-25% stocks in gain to 75%-100% stocks in gain (a drop of about 55%). In parallel, preferences for realizing the worst-ranked stocks increase by approximately 60%. Then, I replicate the main tests conducted in the Sell-Day samples. In Table A6 and Table A7, I show coefficients from the baseline specification and from fixed effects regression models that address omitted variable concerns related to unobserved time-varying account characteristics; and in Table A8, I replicate the sub-samples analyses described above that split the data into sets, each corresponding to different investor and portfolio characteristics. Although estimates are smaller in this sample (because login activity is much more frequent than trading activity), the relative magnitude of the independent rank coefficients and the interaction terms is approximately similar to that documented for the Sell-Days samples. This consistency in the pattern of estimates reinforces the interpretation of my earlier results.

5.3 Portfolio Performance and the Disposition Effect

Collectively, the analyses presented provide compelling evidence for the moderating role of the portfolio performance on rank preferences. The next part of the paper is concerned with providing more direct evidence that rules out the possibility that the disposition effect confounds the reported asymmetric rank effects. Specifically, the next part of the paper focuses on distinguishing the interaction effect between the portfolio performance and rank preferences, discussed above, from the interaction effect between the portfolio performance and the disposition effect that has been studied recently in the literature. In a recent study, An et al. (2019) contrast the disposition effect for paper gain portfolios and paper loss portfolios. The authors' main finding is that the disposition effect diminishes in paper gain portfolios.

Let us first clearly define how our proxies of portfolio performance differ. An et al. (2019) define a portfolio gain dummy that takes the value of one if the investor has a net gain in their holdings (by adding the gains and losses (in dollars) in all their positions as of the given day). Unlike them, I define the portfolio performance by a continuous measure of the proportion of stocks in gain in the portfolio. The reason for this choice is twofold. First, the calculation of proportions demands only simple cognitive processes (i.e., frequency accumulation relative to the total number of stocks). A large body of literature from cognitive psychology has shown that people are fairly good at encoding and manipulating frequencies (e.g., Gigerenzer and Hoffrage, 1995; Sedlmeier and Betsch, 2002). Moreover, the operation of relative frequencies is less demanding when investors hold just a few stocks (the median investor in the data holds only six stocks). Second, in the raw data I observe a monotonic and close to linear decreasing rank effect, rather than a discrete jump, across quantiles in the proportion of stocks in gain. Thus, the use of a continuous measure of portfolio performance provides a more natural representation of investors' rank preferences, which are of primary interest here. Although noting this distinction is important for the proper interpretation of our results, both measures are essentially non-perfect proxies of perceived portfolio performance. Because performance measures under these two definitions are correlated (r=.67), the following comments can be extended to An et al.'s work.

Notice that if the portfolio performance moderates rank preferences, we should expect, as a

side consequence, that the portfolio performance also moderates (mechanically) the well-known disposition effect (though, changes in the disposition effect are not all necessarily ascribed to variations in rank preferences). However, because of the similarity between how these two phenomena operate, given that the best (worst) stock is likely to be a stock in gain (loss), one could question whether the asymmetric rank effects described here are just a rebadging of the traditional disposition effect.

To discriminate between these two phenomena, this section presents further robustness tests that show that investors are willing to sell their best position even if this position corresponds to a stock in loss. The disposition effect cannot readily account for this empirical pattern. Next, I also extend the array of controls of my main econometric specification by adding the interaction between the disposition effect and the portfolio performance (using the proportion of stocks in gain in the portfolio as well as An et al.'s measure of portfolio performance). Together, these two analyses provide convincing evidence for independent effects from these two phenomena.

Beyond providing supporting evidence for the asymmetric rank effect hypothesis, the above exercises point to potential meaningful independent interaction effects between the portfolio performance and the disposition effect, in line with Ai et al's results. Although my primary interest is distinguishing these two phenomena, to prevent the overinterpretation of this secondary set of results, I consider alternative mechanisms that could elucidate this apparent association.

5.3.1 Raw Patterns of the Association Between the Rank Effect, the Disposition Effect, and the Portfolio Performance

Before conducting a formal test of rank effects controlling for the interaction of the disposition effect with the portfolio performance, I plot raw patterns that replicate the key results, but now adding another layer of analysis that separates stocks into winners and losers.

Figure 7 plots the probability of a sale by rank category, portfolio performance, and distinguishing winner from loser stocks for the Barclays Sample. The panels help to visualize any potential interaction across these three dimensions. Blue bars describe the top-two stocks'

selling probabilities, while light blue bars, the bottom-two stocks' selling probabilities. First, the comparison between blue bars in the top panels shows a large (more than 15%) increase in the selling probability when a stock moves from the second position to the top position, even if the sale provides negative profits. While the figure uses the Sell-Days sample from Barclays, patterns using the the LDB Sell-Days sample (Figure B7) are identical, and so are those from the Login-Days Barclays sample (Figure A2). If investors hold pure sign realization preferences (in line with the disposition effect), blue bars on each panel should be uniform. However, we observe a disproportionate preference for the best-ranked stock, consistent with the rank effect hypothesis.

Second, the two right panels in Figure 7 illustrate the interaction effect of the portfolio performance on rank effects, again, even when accounting for sign realization preferences. The comparison of the blue bars on these panels reveals a much smaller distance between the best and the second-best stocks in portfolios of good performance. While the propensity to sell the best stock diminishes, the left panels show the opposite, a small increase in the tendency to sell the worst stock. These empirical observations are consistent with the earlier findings described in Section 5.1.

For simplicity, Figure 7 displays a discrete comparison between two sets of portfolio performance. However, in Figure A3 I illustrate how rank preferences fluctuate over a larger number of sets, over quintiles of portfolio performance. There are important differences to note in Figure A3. The top panels for the best and second-best stocks show substantial (but decreasing) jumps in selling probabilities across quintiles of portfolio performance, with the best stock displaying a much larger variation among the two. The bottom panels for the worst and second-worst stocks reflect, however, much smaller changes in their selling probabilities, which are only perceptible for the worst stock (left panel). In other words, preferences for extreme ranks (i.e., for the best and worst stocks) appear to be particularly sensitive to fluctuations in the portfolio performance.[22]

[22] Similar results are observed in the LDB sample in Figure B8.

5.3.2 Controlling for the Interaction Between the Portfolio Performance and the Disposition Effect

The tables that follow provide a formal test of the two interaction effects associated with the portfolio performance. Table 8 distinguishes the interaction effect between the portfolio performance and rank preferences from the interaction effect between the portfolio performance and the disposition effect that has been documented by An et al. (2019).

Columns 1-3 expand the main specification by adding the interaction between the proportion of stocks in gain in the portfolio and the disposition effect. Adding the interaction has little impact on the qualitative pattern of results. Columns 5-7 reproduce these results using An et al.'s original measure of portfolio performance (a portfolio gain dummy that takes the value of one if the investor has a net gain in their holdings). These findings indicate that investors' concerns for the sign of their profits, moderated by the portfolio performance, are not driving the headline results of the paper.

The table displays two other columns, Columns 4 and 8, that serve as benchmarks for the analysis of the disposition effect and its interaction with the portfolio performance. Columns 4 and 8 illustrate the size of these effects when rank preferences are not accounted for. Comparing these specifications with Columns 3 and 7 suggests a considerable attenuation on the disposition effect coefficients once we introduce rank controls. The interaction effect between the portfolio performance and the disposition effect is halved in Columns 3 and 7. The independent effect of the disposition effect is also diluted (by over 40%) when rank preferences are taken into account. This reduction is more evident in the LDB sample (Table B12), with a drop in the effect size of between 60% to 70%.[23] Thus, rank preferences account for much of the effects attributed to the disposition effect or to its interaction with the portfolio performance.

Notwithstanding the attenuation of the disposition effect coefficients, Table B12 still displays relatively sizeable and significant interaction terms with the portfolio performance, in line with An et al.'s results. To prevent the overinterpretation of these secondary findings, the next paragraphs comment on potential alternative mechanisms that could mechanically produce this association.

[23] An et al. (2019) use a subset of the LDB data—-albeit a larger subset than the LDB sample studied in this paper since the authors do not need to restrict their analysis to portfolios containing five or more stocks. Because large portfolios have low selling probabilities when analyzed at the account × stock × day level, we should expect lower coefficients in the LDB sample than those reported by An et al. (2019).

5.3.3 Alternative Mechanisms for the Interaction Between the Portfolio Performance and the Disposition Effect

An et al's test the interaction effect by pooling the data at the account × stock × day level and adding an interacting term between a portfolio gain dummy and a gain since purchase dummy into the traditional disposition effect regression. Although pooling the data at the investor stock day level constitutes the standard framework applied in the literature, because it ignores the investors' tendency to sell a few stocks (often one or two stocks) irrespective of the portfolio size, it doesn't allow for a clean identification of the interacting effect the authors are concerned with.

To illustrate this point, notice first that rank preferences can mechanically recreate, on their own, the interaction effect between the portfolio performance and the disposition effect. Imagine a group of investors, with varying portfolio compositions of winner and loser stocks, who hold preferences for realizing their best stocks. If they sell only one stock on every trading day (as we often observe empirically), we will estimate that the disposition effect for those investors with portfolios in gain (i.e., a large proportion of stocks in gain) will be smaller than for those with portfolios in loss. This result is a mechanical artefact that arises from investors realizing only one stock on each trading day. When investors hold a portfolio with a higher proportion of stocks in gain, the proportion of realized gains will be by construction small. When they hold a portfolio with a higher proportion of stocks in loss (that still contains a few stocks in gain), the proportion of realized gains will be by construction large. Moreover, pure rank preferences for the best stocks are not necessary for this negative interaction to hold. Similar results arise if investors are more inclined to liquidate their worst-ranked stocks. This negative interaction holds also under our asymmetric rank hypothesis, under which the preference for the best stocks diminishes in portfolios composed mainly by winner stocks.

Second, this mechanical interaction holds too if, instead of rank preferences, we assume investors make a gain-loss choice every trading day (i.e., they first choose whether they want to sell a stock in gain or loss, a gain-loss choice), to then decide which stock from the selected domain they would prefer to sell (as in the two-stage decision model proposed by Sakaguchi

et al., 2019).[24]

Figure A4, Panel A, graphs the (simulated) selling probabilities for 27 different investors that differ in their portfolio composition (from 10% to 90% of stocks in gain) and in their preferences for realizing a gain on the day. Selling probabilities are calculated at the investor × stock × day level, as is usual for analysis of the disposition effect. For each investor, there are 10,000 observations (1000-days ×10-stocks). Given that empirically retail investors often trade only one stock on each trading day, in the simulated data investors sell only one stock a day, and preferences are defined at the day level (i.e., everyday investors make a gain-loss choice). I consider three types of investors with varying degrees of loss aversion, from loss tolerant (left panel) to loss averse (right panel). For instance, a loss tolerant investor with a preference for realizing a gain of .3 (left panel) will realize one stock in gain on 30% of the selling days, and on the remaining 70% of days, one stock in loss. Blue bars show the probability of realizing a gain; grey bars, the probability of realizing a loss. The difference between these two bars is referred to in the literature as the disposition effect.

The top panel shows that when investors expose any consistent preference for realizing gains at the day level (even if that preference is small as it is in the left panel), the probability of selling the stock is mechanically related to the portfolio composition, even though, by construction, the portfolio composition is irrelevant for the gain-loss selling choice on each day. The bottom panel, however, provides a clearer representation of the data, displaying selling probabilities computed at the investor × day level (i.e., the proportion of selling days in which investors realized a stock in gain/loss), which, as expected, reflect no interaction with the portfolio composition.

These cases highlight the fact that a negative interaction between the disposition effect and the portfolio performance can emerge even when the portfolio performance has no direct influence on investors' trading preferences. My earlier results rule out the possibility that pure rank effects or interactive rank effects might be driving An et al's findings. There remains the question whether gain-loss day level choices could confound their findings. The following

[24] Generally, two-stage decision processes are supported by evidence that people naturally engage in within-domain comparisons when they evaluate outcomes (i.e., they naturally consider a context of similar outcomes for comparison, such as losses against other losses) (McGraw et al., 2010).

observations might help rule out the special case of *pure* gain-loss day level choices (as described above), but do not rule out the possibility of a mixture of gain-loss day level choices with other trading heuristics. For a deeper discussion on some of these alternative mixture-models and evidence of how they can enhance fitting quality of the disposition effect data, see Sakaguchi et al. (2019).

To test for *pure* gain-loss day level choices, I collapse the data at the account × day level and compute the proportion of selling days in which investors liquidated any winner stocks minus the proportion of days in which they liquidated any loser stock. For simplicity, I label this measure as the day-level preference for winners. If the gain-loss (day level) choice hypothesis is correct, the day-level preference for winners should be invariant to fluctuations in the portfolio composition. Figure A5 plots the day-level preference for winners in the Barclays sample. Contrary to these predictions, the data expose the opposite: a positive association between the day-level choice for winners and the proportion of stocks in gain in the portfolio.

It may be helpful to outline the intuition behind these results under the asymmetric rank effect hypothesis. If investors' rank preferences fluctuate in a way that when they hold a portfolio in loss, they are eager for liquidating their best stocks, but when they hold a portfolio in gain, they become indifferent between their extreme ranked stocks (i.e., their preferences for their best-ranked stocks attenuate and show some shifts towards their worst-ranked stocks). Then, on days when their portfolio is in loss, the day-level disposition effect will be large. However, on the days when their portfolio is in gain, the investor will be about equally likely to select between their best or their worst positions. Because winner stocks are more common in this second case, their rank preferences will lead to a sizeable proportion of selling days where a winner stock was sold, or a large day-level disposition effect too. The combination of these two results can lead to a day-level disposition effect that is much larger when investors hold paper gain portfolios.

It is important to acknowledge that although the data do not appear consistent with investors making *pure* gain-loss day level trading choices, it may nevertheless be compatible with a mixture of gain-loss day level choices on some trading days and the random selection of

stocks in others[25]. Testing for this alternative or any other combination of trading heuristics is outside the scope of this paper.

While my extended analysis provides some support to An et al.'s findings, it is essential to emphasize that the goal here has not been to explicitly test the interaction effect of the portfolio performance and the disposition effect, but rather to articulate some alternative mechanisms for this interaction and, fundamentally, wary researchers of some other potential confounds and limitations that derive from neglecting retail investors' low trading activity regardless of their portfolio size.

This section has examined in more detail the differences between the primary results of this paper and the interaction effect between the portfolio performance and the disposition effect documented by An et al. (2019). The next section discusses some possible mechanisms by which the portfolio performance moderates rank effects.

5.4 Rank Effect Mechanisms

5.4.1 Portfolio Rebalancing

Let us consider first some rational (psychology-free) reasons why investors may display patterns consistent with the asymmetric rank effect hypothesis. One potential explanation for the interacting rank effects might be portfolio rebalancing. If an investor has many stocks in loss and only a few in gain, the best performing stock may denote a higher weight in the portfolio. In such circumstances, the investor might be inclined to reduce their position in that stock in order to minimize their risk exposure. While such rebalancing strategies might explain partial sell-offs, they are often not consistent with liquidations of stocks' entire positions.

I test for this possibility by restricting the analysis to complete sales (i.e., liquidations of positions), thereby excluding partial sales, which might indicate a desire to rebalance portfolios (following the same treatment used by Odean, 1998). Table A10 replicates Table 4, but now with the use of a restricted dependent variable indicating complete sales. The coefficient estimates across columns are in line with those in the main results, with the best stocks showing negative interactive rank effects. This result suggests that the asymmetric rank effects do not arise from

[25] Or perhaps the combination of one-stage and two-stage models, as findings from Sakaguchi et al. (2019) suggest.

the desire to rebalance the overall portfolio. The same conclusions hold for the LDB sample in Table B13.

5.4.2 Tax-Motivated Selling

A second potential explanation might be tax-motivated selling, whereby investors with potential large capital gains might choose to sell their loser stocks near the end of the tax year because of the tax benefits of doing so. The Barclays Stockbroking platform offered a range of account types, all of which were execution-only, but differed in taxable status. In the baseline sample, about 50% of accounts are tax liable direct investing accounts. Nevertheless, tax-motivated selling is likely to be minimal because of the amount of tax-free allowance for capital gains available, which was between £10,600 and £11,100 throughout 2012-2016. Since in the data, 90% of investors' trades are below £9,980, and 50%, below £2070, most investors would not be concerned about paying tax on their investment income.

Nevertheless, I test for the possibility of tax-motivated selling in two ways. First, I reproduce the main analysis but exclude from the sample the month before the end of the year (in the UK, the tax year ends on 5 April), when tax loss selling is more likely to occur. Second, I also replicate the main analysis on the subset of tax-exempt accounts. This second exercise restricts the analysis to 2249 accounts, which include principally Retail Individual Savings Accounts (ISA). ISA investments are non-tax accruing, with caps on maximum annual investment amounts.[26]

Table A12 presents the results from these two exercises. Columns 1-3 show the expected rank effects in the sample that excludes the month prior to the end of the tax year. Columns 4-6 reproduce the main headline of results in the subset of tax-exempt accounts. Both results suggest that tax considerations cannot explain the interactive rank effects observed in the data. The same conclusions can be reached in the LDB sample. Table B14 restricts the LDB sample to 1,310 tax-exempt accounts, including IRA and Keogh accounts.

[26] A small proportion of 16% of accounts are money-purchase Self-Invested Personal Pensions (SIPP), which are also non-tax accruing.

5.4.3 Expectations About Stocks' Returns

The patterns we observe in the data could also reflect the beaviour of investors who extrapolate the past growth of their most salient stocks (e.g., their extreme-ranked stocks). Investors may believe that returns of their best-performing stocks may move back towards their long-run average (or mean revert). Moreover, recent evidence characterize retail investors as contrarians around news announcements, selling stocks on large positive earnings surprises and buying stocks on large negative earnings surprises (Luo et al., 2020). Investors holding mean-reverting beliefs about their stocks with abnormally high positive returns may intensify those beliefs when they experience losing portfolios and so be prone to sell.

Investors may also form beliefs about the performance of their worst-ranked stocks. Observing that their investment thesis has failed to develop as expected, investors may revise downward their beliefs about the stocks' fundamentals and decide to sell. Holding portfolios in gain might exacerbate this revision since low-performing stocks would be more distinguishable from the other stocks in the portfolio. Note that in both situations, with losing or winning portfolios, experiencing abnormal returns will also help investors to rationalize (and therefore justify) their selling decisions.

In Figure A6, I provide a set of empirical evidence that my results are not dependent on the pattern of returns investors recently experienced, which are more likely to drive their beliefs about future returns. The figure reproduces the main result for sub-samples of observations split by whether the stock was in gain (bottom sub-plots) or loss (top sub-plots) since the previous week (Panel A), month (Panel B) or quarter (Panel C). Each panel yields the same selling pattern: portfolios in gain motivate the sale of the best stock, and portfolios in loss attenuate the gap between the best and worst stocks. The pattern emerges regardless of the sample under analysis (see Figure B9 for results using the LDB sample).

5.4.4 Psychology-Based Explanations

Let us now consider two potential psychology-based explanations for the findings: varying degrees of risk aversion over time that follow fluctuations in investors' portfolio performance; and mood self-regulation trading strategies.

The first mechanism incorporates the possibility that investors derive utility from both the (paper) gains in their portfolio as well as the realized gains from stocks liquidations. However, they evaluate these two in two different "choice brackets"—because if they were part of the same mental account, that is, if the gains/losses from an individual stock were integrated with the rest of the investor's portfolio, then realized losses from individual stocks would be relatively inconsequential (particularly in large portfolios) to induce significant effects on subsequent trading behaviour, which would contradict vast evidence on the investors' tendency to sell stocks trading at a gain and hold stocks trading at a loss (i.e., the disposition effect, Shefrin and Statman, 1985; Barberis and Xiong, 2012).

A growing body of research recognizes the possibility that investors derive utility from fluctuations in the value of their holdings (or their financial wealth) and that the utility generated by wealth fluctuations could go beyond the indirect utility associated with anticipated changes in future consumption, e.g., at the moment investors observe that their portfolios are doing poorly, they might feel vulnerable and lacking confidence in their trading abilities (Barberis, 2018; Barberis et al., 2001). Moreover, investors who have already acknowledged their portfolios' poor performance might still derive utility from the mere act of attending to their portfolios. Recent empirical work shows that investors derive utility purely from the act of looking at information, even if this brings no news to them. Quispe-Torreblanca et al. (2020), after studying the portfolio look-up behaviour of retail investors (using a larger sample of brokerage data provided by Barclays Stockbroking)[27] show that individuals devote disproportionate attention to already-known positive information about changes in the prices of their stocks. The authors coin the term "Attention utility" to describe the hedonic pleasure, or displeasure, derived purely from looking at, or thinking about (savouring), information. These findings complement earlier research on information avoidance (and models of beliefs-based utility), under which individuals attempt to make attention decisions to protect themselves from receiving information they suspect may be adverse (for examples, see Karlsson et al., 2009; Sicherman et al., 2016). Together, these studies emphasize the possibility that fluctuations in

[27] Quispe-Torreblanca et al. (2020) analyse the look-up behaviour of approximately 87,000 accounts provided by Barclays Stockbroking. This sample includes, to a large extend, the baseline sample studied here, which is restricted to accounts that open after the beginning of April 2012 (accounts for which I observe the purchase price on all stocks held within their portfolios).

portfolio values may induce immediate hedonic utility (or emotion swings).

Considering all of this evidence, a first interpretation of the patterns identified in the data is that investors attending to poor performing portfolios would become warier of experiencing additional losses. On the contrary, those attending well-performing portfolios would be less apprehensive of realizing a loss, which is now cushioned by the hedonic utility derived from attending to their portfolios. This view is consistent with experimental evidence provided by Thaler and Johnson (1990), who demonstrate that a loss is less painful to people when it comes after a substantial prior gain (the house money effect). Prior losses, on the other hand, make people more risk-averse to gambles that risk additional losses.

Imas (2016) offers important insights for the understanding of how prior outcomes affect risk attitudes. When evaluating gambles, if the decision maker can integrate (in the same choice bracket) his prior losses with potential future payoffs, then gambles that allow him to erase prior losses become more attractive. Using the author's stylized example as an illustration of the main idea, suppose that the decision maker takes a gamble with a one-third chance of winning $250 and a two-thirds chance of losing $100, and suffers a $100 paper loss. If offered the same gamble again, he now compares the sure $100 loss, if he turns the second gamble down, with the prospect of either winning $250 or losing $200 if he accepts the second gamble. Since the second gamble allows him to avoid realizing the sure loss, he now strictly prefers to take the gamble. However, if the $100 loss was realized (i.e., cash was discounted from his account immediately after the gamble was played out), he internalizes the negative outcome, experiences the pain of loss, and closes the associated choice bracket. Then, the prospective second gamble is evaluated in a new choice bracket, making the decision maker become more loss averse. As the author points out, this enhanced loss aversion may be due to the increased salience of the potential subsequent loss (Bordalo et al., 2012, 2013) or perhaps the reduced capacity for dealing with bad news about future consumption (Kőszegi and Rabin, 2009; Pagel, 2017).

In the framework of the above example, a realized loss involves the closure of the associated choice bracket and so it cannot be integrated with the second prospect. However, the analogy I make here is subtly different. Although portfolio changes correspond to either paper losses or

paper gains, because they induce a burst of utility at the moment investors observe them, as the research described earlier on attention utility and information avoidance suggests, we could treat them as realized gains or losses in Imas's example. That is, we can posit that because investors experiencing the pain of admitting that their portfolio is in loss are no longer able to integrate these changes in utility with subsequent prospects, their aversion to risk will increase, making them prone to sell their best positions under the fear of further future losses. Essentially, the first potential (psychology-based) mechanism is based on changing risk-aversion as the investors' portfolio performance fluctuates over time.

Notice that while we could speculate that this increased risk aversion might raise the selling probability homogeneously for every stock in gain in their portfolio, rather than just for the best positions, the empirical patterns point toward an uneven effect across stocks. Investors often sell one or two stocks on any given trading day, even when they hold large portfolios, and are the stocks with extreme ranks the ones that show the largest changes in selling probability. Thus, these patterns conform well to those described by the asymmetric rank preference hypothesis.

A second possible explanation for the results might be that investors are making selling decisions in order to self-regulate their mood. A large body of literature studying the influence of affect, or feelings, on decision making, including experimental work by Isen and colleagues, shows that individuals in whom positive affect had been induced are reluctant to gamble, sometimes avoiding significant large stakes and even when there is greater optimism about the prospect of winning. (e.g., Isen and Patrick, 1983; Isen et al., 1988; Isen, 2000). These studies support the hypothesis that individuals make decisions aimed at safeguarding their affective state (mood maintenance hypothesis).

Here, we might imagine that investors observing their portfolio in loss, in an attempt to recover their affective state prior to becoming aware of the poor performance of their portfolio, will be tempted to liquidate a positive position. Then, selling the best performing stocks could be a strategy aimed to offset the mood effects induces by observing portfolios in loss.

If mood maintenance strategies are prevalent in the data, we should expect that portfolios in loss are followed by either the realization of winner stocks or, if not available, the reluctance

to trade on the day. However, the evidence discussed in Figure 7, revealing that investors are willing to sell their best positions even when they correspond to stocks in loss, casts doubt on the validity of this second mechanism.

The caveat to these two mechanisms is that I cannot rule out the possibility that emotions (or mood) might affect investors' cognitive functions or other intrapersonal factors, such as motivation, that could influence their trading skills (by biasing beliefs about probabilities of attaining gains, for example) and lead to apparent changes in risk preferences. In the context of this paper, as in most empirical work in asset pricing, distinguishing whether changes in trading behaviour are driven by emotions influencing risk preferences or rather by the influence of emotions on the cognitive evaluation of prospects is difficult.

Irrespective of such ambiguity, the evidence presented here supports the basic proposition that investors experience a burst of negative utility at the moment they observe their portfolio in loss, which leads to more risk-averse choices, e.g., selling their best positions under the fear of further losses.

5.4.5 The Role of Salience (Uncorrelated with Economic Factors)

I now move onto studying the role of salience in producing the reported asymmetric rank effects. An intuitive explanation for the rank effect is that extreme positions are more salient (or more attention grabbing) in the investors' portfolios. While salience may constitute an essential determinant of the rank effect, the mechanisms discussed above are agnostic as to whether portfolio fluctuations will increase trading in stocks with a salient characteristic unrelated to what the investors' choice brackets or mental accounts are balancing off (i.e., unrelated to stocks' gains and losses).

To establish whether salience itself (orthogonal to any economic explanation) can induce rank effects, Hartzmark (2015) tested the effects of an alternative rank order based on the alphabetical order of companies' names—exploiting the fact that stocks are often displayed in this order online or in brokerage statements. He documents that the first and last positions, by alphabetical order, have higher selling probabilities than the middle positions. Following this set of results, I now examine the interaction effect of the portfolio performance and the

referred alphabetical rank effect on stock sales.

I begin by showing estimates of Equation 1 using these alternative rank variables. For a proper comparison with the original (alphabetical) rank effect estimates, this analysis is computed on the LDB sample. Table B15 displays rank coefficients from different fixed effects specifications. In general, there is an apparent inconsistency between these rank coefficients and our prior set of results that use ranks defined based on returns. For instance, across columns, we observe larger effects, albeit imprecise, for the second name than for the first name. Although a few rank coefficients are significant in Columns 1 or 2, when investor and stock heterogeneity is considered in the estimation (Column 3), we find null effects for each rank position and their interaction terms. While null effects for the interaction terms might not be surprising (as the mechanisms described above provide no priors that could suggest the opposite), null effects on the independent rank coefficients are intriguing.

To account for the possibility that alphabetical rank effects exist but are limited to large portfolios, I analyse raw trading patterns of different subsets of the data split by portfolio size. Table B16 displays the unconditional selling probabilities for each alphabetical position. Column 1 pools all observations in the sample. Columns 2 to 5 limit the sample to portfolios of 5, 7, 9 and 11 stocks, respectively. Column 1 shows significant and sizeable rank effects: the first name-middle name and the last name-middle name gaps are of about six percentage points (representing changes of about 50% in the average selling probability of the sample). However large these effects appear to be, notice that a large portion of these effects could be due to the mechanical artefact induced by pooling together portfolios of different sizes. Columns 2 to 5 address this concern by restricting the sample to portfolios of the same size. These columns confirm the conclusions reached in Table B15 above that the order of company names has no meaningful effect on the propensity to make a sale. Notice that the magnitude of the first name-middle name and the last name-middle name gaps is close to zero, and the sign of these gaps appears erratic across columns.

As an additional check, I re-estimate Table 8 from Hartzmark (2015). In Columns 1 to 3 of Table B18, I reproduce the original alphabetical rank estimates, i.e., a larger tendency to sell

the first and last positions by alphabetical order.[28] However, these rank effects have their size halved after adding a linear control for the portfolio size in Columns 3 to 4; and are undetectable once we allow for a more flexible treatment of time-varying account heterogeneity in Columns 4 to 9.

Although the latter result was unexpected, it is important to acknowledge that I find the alphabetical rank effect hypothesis plausible and compatible with potential primacy and recency effects in memory if investors study their portfolio of firms from the top to the bottom of the list displayed in their screens; and compatible too with alphabetical bias effects reported in other domains.[29] However, the hypothesis doesn't appear to hold in the underlying data.

5.5 The Relation with the V-shaped Selling Propensity

Up to now, the discussion has turned around rank effects. We now move on to examining the implications of the primary mechanism discussed above on a particular phenomenon: the asymmetric V-shaped selling propensity in response to unrealized profits (i.e., the observation that the investors' selling probability increases as the magnitude of gains and losses increases, with a steeper slope for gains than for losses, documented by Barber and Odean, 2013, Ben-David and Hirshleifer, 2012, and Seru et al., 2010). This is a well-known phenomenon, however, not fully understood. Its elucidation is important because, as findings from An and Argyle (2020) point out, this trading behaviour can impact equilibrium price dynamics and generate subsequent return predictability in the cross-section. The most accepted explanation contends that the V-shaped pattern arises from speculative trades who revise their beliefs about the future performance of their stocks when large price movements occur (Ben-David and Hirshleifer, 2012).[30]

[28] See Table B17 for a copy of Table 8 in Hartzmark (2015).

[29] The literature provides some pieces of evidence in favour of the primacy effect hypothesis. For instance, Einav and Yariv (2006) and Van Praag and Van Praag (2008) show that faculty with earlier surname initials are more likely to receive tenure at top ten economics departments. Merritt (1999) shows similar findings for the likelihood of spending one or more semesters visiting another school among law faculty. In the finance literature, Itzkowitz et al. (2016) and Jacobs and Hillert (2016) document that US firms positioned early in an alphabetically ordered list (e.g., NYSE/Amex/Nasdaq firms) have higher trading activity and liquidity.

[30] Alternative explanations for this phenomenon are given by Meng and Weng (2018), with a model in which investors who hold prospect theory preferences use as reference points their expected final wealth; and by Ingersoll and Jin (2013), whose model can predict a V-shaped selling pattern as an aggregation effect of heterogeneous investors who also display prospect theory preferences.

In this section, I propose a complementary but distinct view of this phenomenon, namely, that it stems in part from investors changing their risk attitudes when their portfolio performance fluctuates over time. Following the logic of the primary mechanism discussed earlier, we can expect that experiencing losing portfolios would induce higher levels of risk aversion and therefore a larger probability of selling stocks with large positive returns in the aggregated data. Likewise, experiencing portfolios of good performance would increase risk taking attitudes, inducing some shifts towards liquidating stocks with large negative returns and attenuating (but not eliminating) preferences for large positive returns (given that both positive and negative extreme returns are more salient to the investor). More generally, it is intuitive to expect that preferences for extreme-ranked stocks and preferences for extreme returns should move in the same direction, as they both highlight attention grabbing characteristics related to stocks' returns. The following set of results appear to confirm this intuition.

To ease the comparison with the results reported in Ben-David and Hirshleifer (2012), I start by showing patterns in the LDB sample. Figure 8 shows binned scatter plots that plot selling probabilities over four different holding periods: less than 30 days, 31 to 100 days, 101 to 300 days, and over 300 days. Because rank preferences are not of main interest here, the sample includes portfolios with two or more stocks. For holding periods less than 30 days, we observe a V-shaped selling pattern with the right branch for positive returns being steeper than the left branch for negative returns. As documented by Ben-David and Hirshleifer (2012), this pattern diminishes over time.

We now analyze the association between this pattern and investors' portfolio performance. Figure 9 distinguishes portfolios in loss from portfolios in gain. To be as detailed as possible, each subpanel in the figure reports the proportion of observations and the proportion of trading days that are used for the analysis[31]. These proportions indicate that, for each holding period, observations are nearly evenly distributed across sub-panels of portfolios in gain or loss, and so that each subpanel is roughly equally important in producing the aggregate results we observe in Figure 8. Comparing the sub-panels of portfolios in gain (Columns 1 and 3) with those of portfolios in loss (Columns 2 and 4), the V-shaped selling pattern appears to be specific to

[31] Including the proportion of trading days is informative as large portfolios are mechanically overweighted by offering more observations to the analysis.

the trading days on which investors face well-performing portfolios, in accordance with the main behavioural mechanism sketched above. The pattern weakens as the time since purchase increases; however, it is detectable even for the largest holding period plotted. The moderating role of the portfolio performance appears to be more prominent in the Barclays sample (see Figure A7 and Figure A8). These results suggest that both rank preferences and preferences for extreme returns point towards the same mechanism, under which the hedonic impact of fluctuations in portfolio performance will provoke immediate changes in risk attitudes that are manifested more strongly in sales of stocks with salient returns.

6 Conclusion

In this paper, using detailed data on investors' trading activity and portfolio performance from two distinct datasets, I show that the patterns which prior literature has attributed to preferences for selling both the best and the worst ranked stocks (i.e., rank effects) can be traced to different responses of investors when their portfolio performance fluctuates over time. I show that when investors face poorly performing portfolios, they become predisposed to liquidate their best stocks; otherwise, their rank preferences for their best stocks attenuate and show some shifts towards their low-ranked stocks.

To provide conclusive and compelling evidence for the asymmetric rank effect hypothesis sketched above, this paper starts by describing some methodological constraints in the standard estimation of the rank effect and proposes a new framework with a number of advantages. A drawback of the standard framework is that it ignores investors tendency to liquidate only a small number of stocks, irrespective of their portfolio size. Neglecting this aspect of retail investor data may lead to misleading conclusions. As a noteworthy illustration, a re-estimation of alphabetical rank effects, which have been used as evidence that rank effects may occur due to factors orthogonal to economic variables, reveals null effects.

Although the reader may reasonably argue that the confounds I discuss could be reduced by the inclusion of account $\times$ day level fixed effects, what I want to emphasize is that the widespread practice of relying solely on saturated fixed models to control for unobservables may mask (potentially large) time-varying investors' heterogeneity. First, estimates overweight

the influence of investors that contribute more observations (e.g., those with large portfolios, those who trade frequently, etc.) but who could be less representative of the median investor. Second, this standard practice arguably ignores or at least downplays the quantification of the pervasiveness of the behavioural phenomena under study. Large estimates (e.g., large rank effects) might not necessarily imply that rank effects are prevalent across investors, nor that they are regular across trading days.

The first part of this paper takes a different but complementary angle for the estimation of rank effects. In terms of methodology, I propose a new framework with a number of advantages. It is informative on the prevalence of rank effects across trading days, and it enables the investigation of potential rank extremeness aversion in trading behaviour. The data reveals that on 39% of trading days investors liquidate their best-ranked stocks; while only on 17% of trading days, their worst-ranked stocks. Potential rank extremeness aversion is not trivial, with over 30% of trading days corresponding to sales of stocks from middle positions. Providing estimates of the extent to which rank preferences influence trading patterns is useful for a discipline in which behavioral biases are often understood as systematic and persistent.

Despite the initial focus on the method, the argument developed in this paper should not be understood as a conceptual critique of the original rank effect hypothesis, nor as suggesting that the original rank effect estimates are irrelevant. On the contrary, the evidence presented here shows that once we incorporate the interaction effects of the portfolio performance on rank preferences, we are able to explain a considerable large variation in trading responses. For instance, the preference for the worst-ranked stocks nearly doubles when portfolios move from containing 0%-25% stocks in gain to containing 75%-100% stocks in gain. The extent of these asymmetric rank effects across two different datasets covering two distinct countries and two distant decades strengthens the interpretation of the rank effect as a fundamental aspect of investor behaviour, and complements earlier findings in the literature.

The evidence discussed in the second part of the paper provides strong support for the association between the portfolio performance and the rank effect. This association cannot be justified by rational explanations such as investors' desire to rebalance their portfolio, potential tax-motivated selling, or expectations about future stocks' returns. I argue that the empirical

patterns in the data can be elucidated by assuming that investors derive utility not only from realizing sales but also from monitoring their portfolio (and internalizing their changes in value). Then, fluctuations in their portfolio performance may induce immediate hedonic utility, leading to subsequent changes in risk preferences, where those attending well-performing portfolios would be less apprehensive of realizing a loss, and vice versa.

As discussed, this mechanism is consistent with a growing body of research showing that individuals derive utility purely from the act of looking at, or thinking about, information or their related outcomes; and that prior outcomes influence future risk-taking behaviour by altering the way individuals experience subsequent gains and losses. Beyond providing a link between rank preferences and portfolio performance, this mechanism can also shed light on the asymmetric V-shaped selling propensity in response to unrealized profits. I show that the V-shaped pattern is particularly specific to trading days when investors hold well-performing portfolios.

Although not the focus here, the results of this paper also help to shed light on two key puzzling features of stocks' returns: the excess volatility of returns and the equity premium puzzle. Changes in risk aversion might explain the high volatility in returns, which could be accompanied by persistent losses, making our loss-averse investors require a high equity premium to hold stocks. A more formal framework to explain these puzzles is offered by Barberis et al. (2001). Agents in their model derive utility not only from consumption levels but also from fluctuations in their financial wealth. They are loss averse over these wealth fluctuations. As such, agents' risk aversion changes over time as a function of their investment performance, which generates time-varying risk premia, excess volatility in prices in comparison to the underlying dividends, and eventually large equity premia. These results are also consistent with recent evidence demonstrating that the disposition effect moves countercyclical with the stock market Bernard et al. (2021). If boom and bust cycles correlate with investors' portfolio performance, then part of these fluctuations in the disposition effect may be explained by changes in investors' risk attitudes and rank preferences. More generally, my results provide new insights to a growing literature in behavioural finance documenting behavioural biases exhibited by individual investors, highlighting the importance of emotions and context effects

on decision making.

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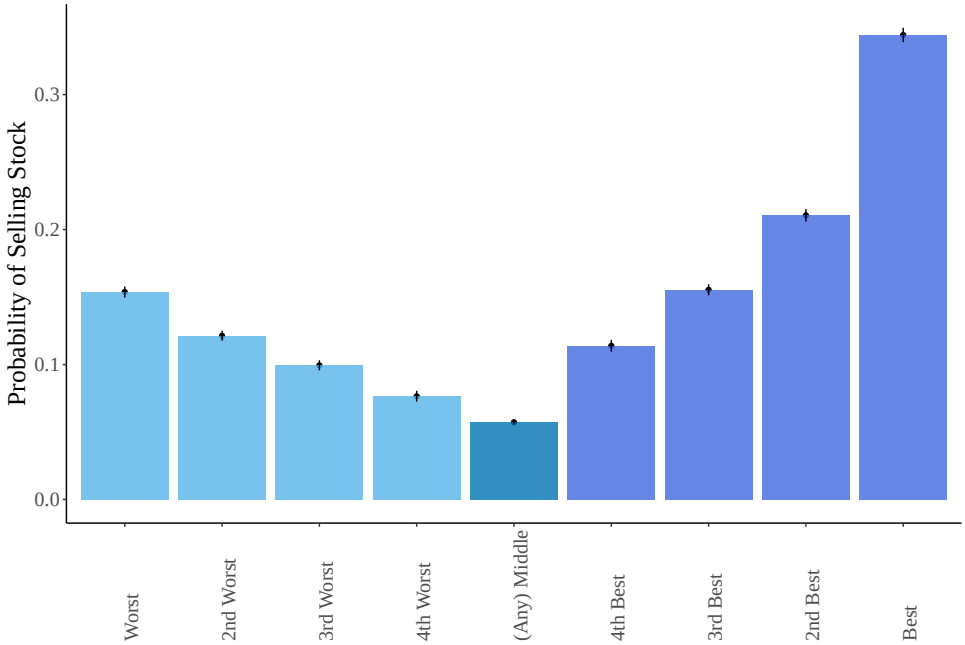
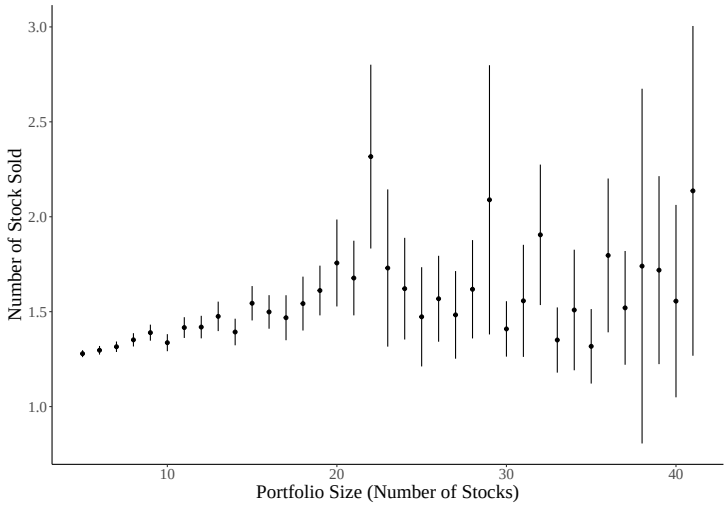
Figure 1: Unconditional Rank Effect, Barclays Sell-Day Sample



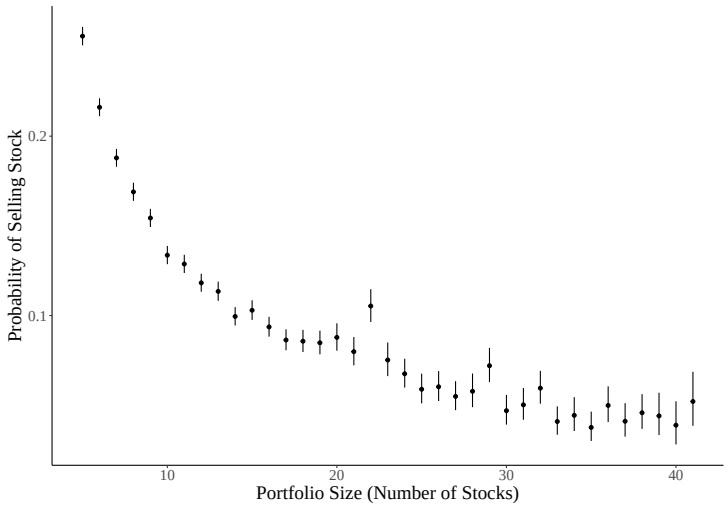
Note: The figure shows the unconditional probability of a sale based on rank positions. Observations are at the account × stock × day level. The sample includes days in which the investor made at least one sale. Each bar represents the ratio of stocks that are sold in the indicated category divided by all stocks in that category. For example, the *Worst* bar reports #Worst Sold/(#Worst Sold + #Worst Not Sold). Vertical lines represent 95% confidence intervals.

Figure 2: Number of Stocks Sold on a Trading Day by Portfolio Size, Barclays Sample

(A) Numbers of Stocks Sold on a Trading Day

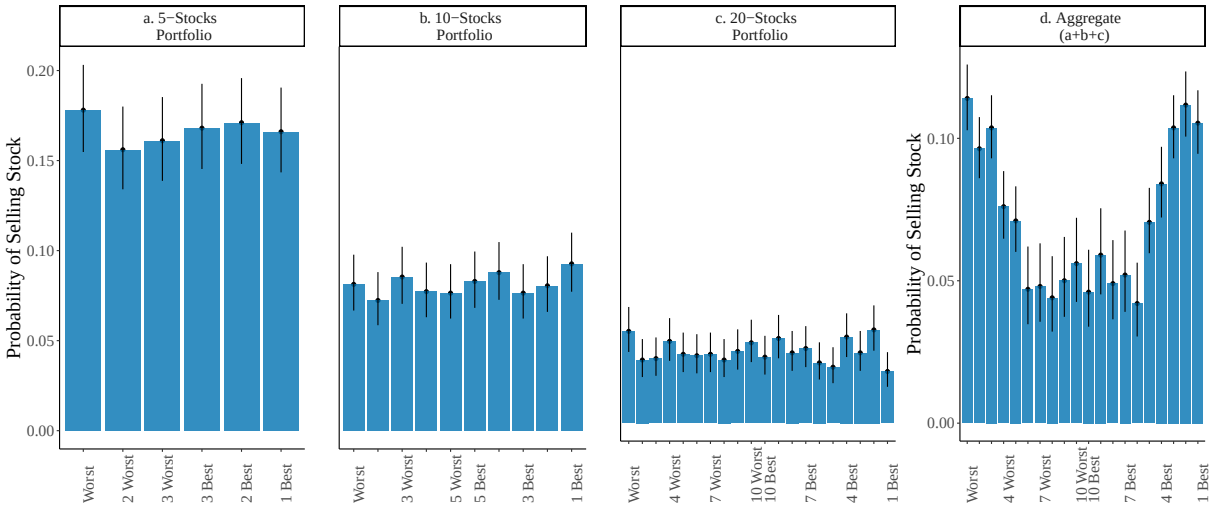


(B) Probability of a Sale



Note: The figure shows the frequency of sales by portfolio size. Panel A displays the average number of stocks sold on a trading day by portfolio size. The sample includes days in which the investor made at least one sale. Panel B shows the probability of a sale using observations at the account × stock × day level. For a better visualization, outliers at the 99th percentile of portfolio size were excluded. Vertical lines represent 95% confidence intervals.

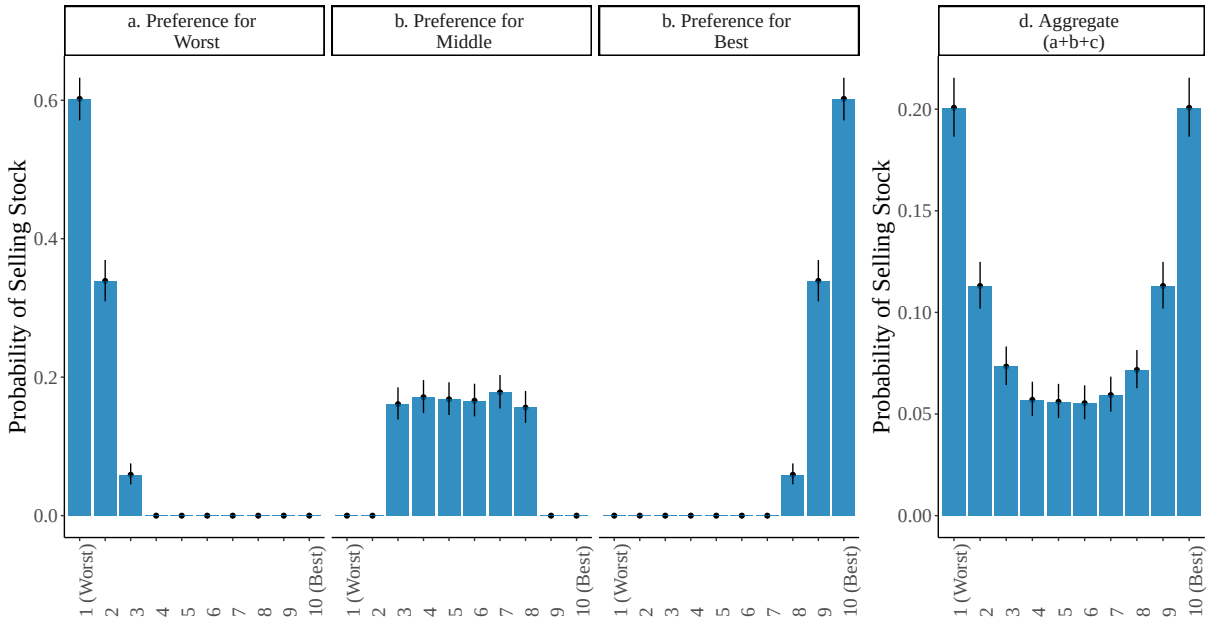
Figure 3: Simulated Selling Probability by Portfolio Size



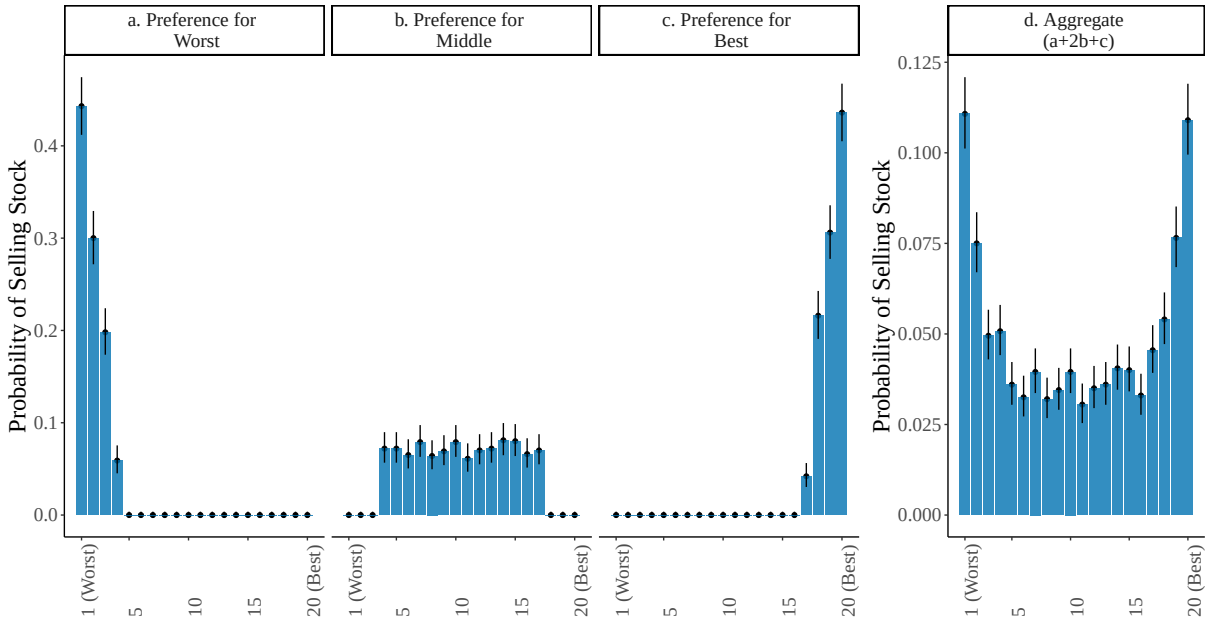
Note: The figure shows simulated distributions of selling probabilities by rank preferences. Probabilities are computed using observations at the account × stock × day level. Plots (a), (b), and (c) show each the probability of a sale for three investors with different portfolio sizes, assuming that each investor selects one stock randomly each day (i.e., they have no rank preferences). The data includes 1,000 simulated selling days for every investor. Panel (d) plots the probability of a sale for the aggregated data. Vertical lines represent 95% confidence intervals.

Figure 4: Simulated Selling Probability by Investor's Preferences

(A) 10-stocks portfolios

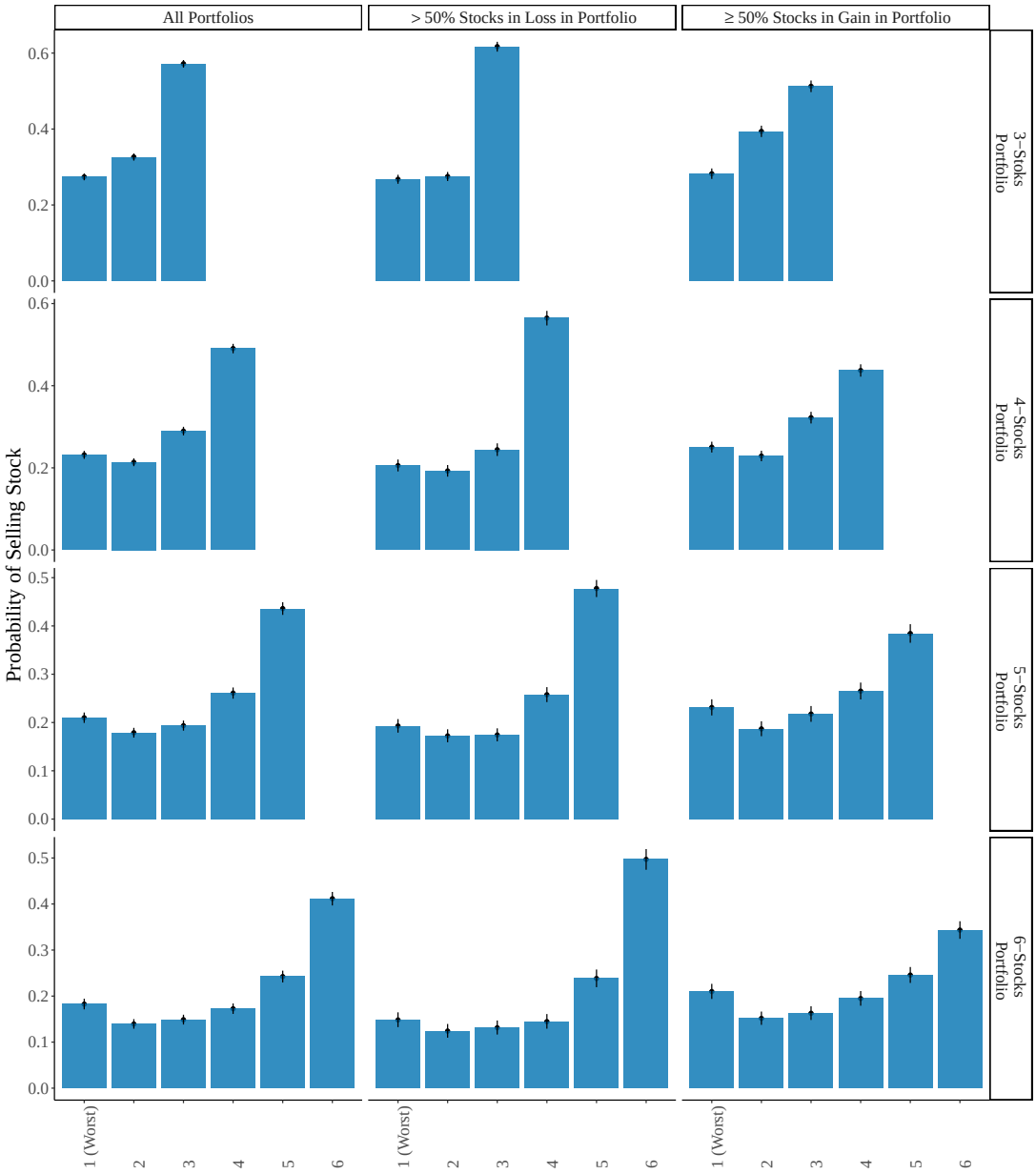


(B) 20-stocks portfolios



Note: The figure shows simulated distributions of selling probabilities for three investors with different rank preferences. Probabilities are computed using observations at the account × stock × day level. In the top panel, plots (a), (b), and (c) show each (simulated) selling probabilities for 1,000-selling-days × 10-stock-portfolios (10,000 observations for each investor). In the bottom panel, the portfolios contain twenty stocks instead of ten. In the top panel, when the investor has preferences for the best (worst) ranked stocks, one stock is drawn each day from the portfolio set with probability weights 0.60,0.35,0.5 in the top panel for the three stocks with the highest (lowest) ranks, and with zero probabilities for the remaining stocks. In the bottom panel, these probabilities are 0.45,0.30,0.20,0.05 for the four stocks with the highest (lowest) ranks. When the investor has an aversion to extreme ranked stocks (i.e., preference for the stocks in the middle but with no particular interest in one of these stocks), the six stocks (14 stocks) in the middle receive uniform probability weights in the top panel (bottom panel). Plots in the fourth column display selling probability for aggregate samples composed by (a), (b), and (c) in the top panel; and (a), 2(b), and (c) in the bottom panel. Aggregate samples, despite including different structures, expose identical patterns. Vertical lines represent 95% confidence intervals.

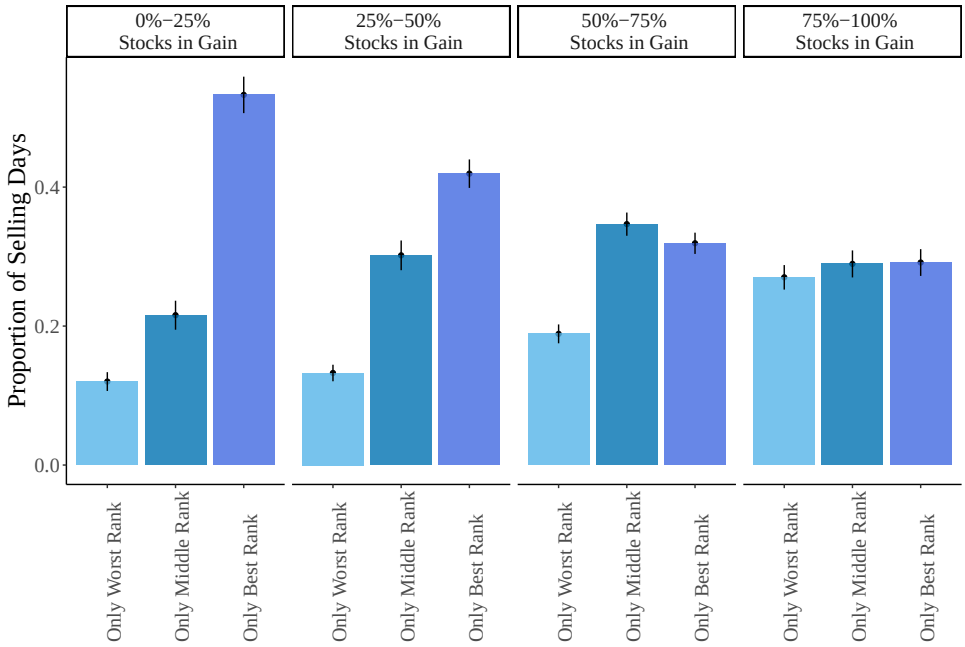
Figure 5: Probability of Selling Stock for Small Portfolios, Barclays Sell-Day Sample



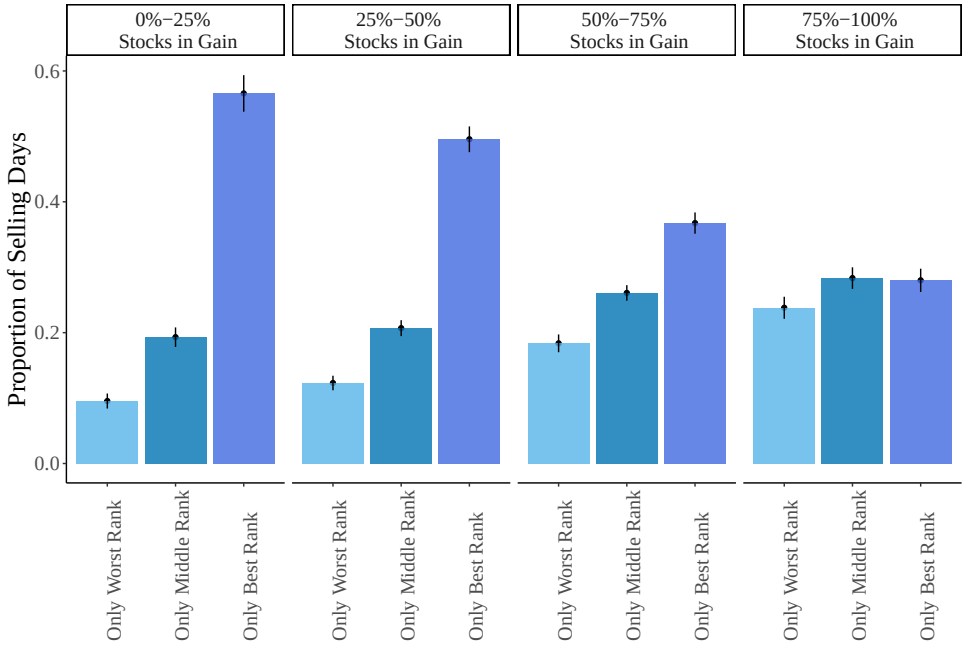
Note: The figure shows selling probabilities for small-size portfolios. Portfolios of between three to six stocks are included separately across rows. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Each bar represents the probability of a sale in the indicated rank category. Column 1 aggregates all portfolios. Columns 2 and 3 split the data by portfolio composition. Column 2 includes portfolios composed mainly of loser stocks. Column 3 consists of the remaining portfolios. Vertical lines represent 95% confidence intervals.

Figure 6: Proportion of Selling Days by Portfolio Composition, Barclays Sample

(A) Best/Worst Ranks Defined as the Top/Bottom Two Positions

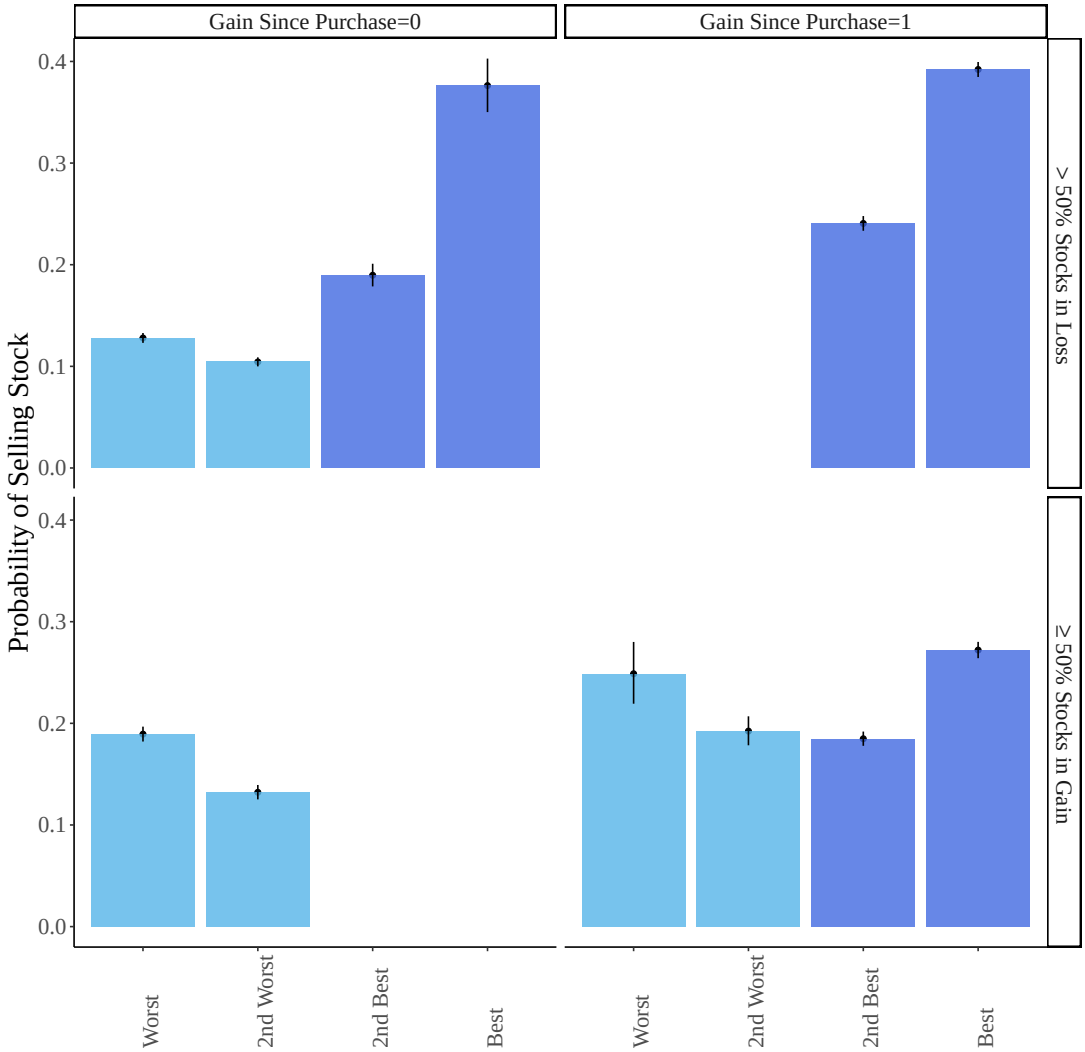


(B) Best/Worst Ranks Defined as the Top Tercile/Bottom Tercile Positions



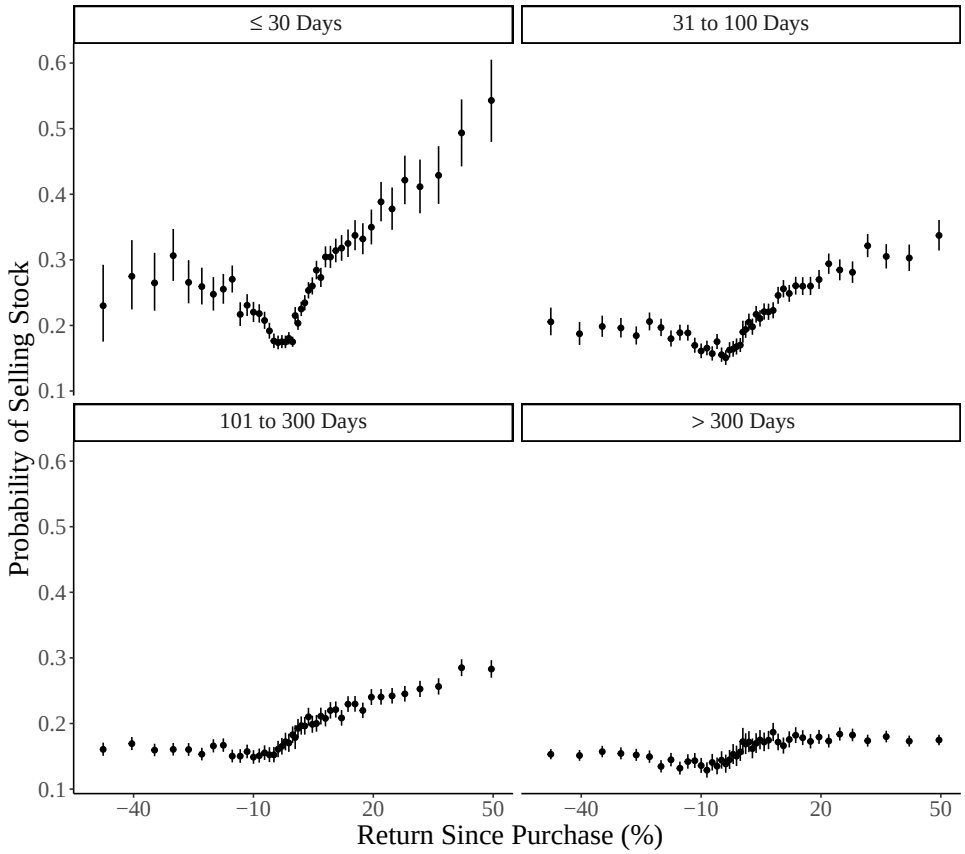
Note: The figure shows rank preferences using data at the account × days level. The sample includes days in which the investor made at least one sale. Panel A shows the proportion of sell days in which the investor sold stocks exclusively from the top two positions (*Only Best Rank*), the bottom two positions (*Only Worst Rank*), or positions in between (*Only Middle Rank*). Sub-panels split the sample by the proportion of stocks in gain in the portfolio. Column 1 includes days in which over 75% of stocks in the portfolio were in loss; likewise, Column 4, days in which over 75% of stocks were in gain. Panel B repeats the same exercise, but now rank categories are defined based on terciles of the rank distribution. Vertical lines represent 95% confidence intervals.

Figure 7: Probability of Selling by Portfolio Compositions and Gain Since Purchase, Barclays Sell-Day Sample



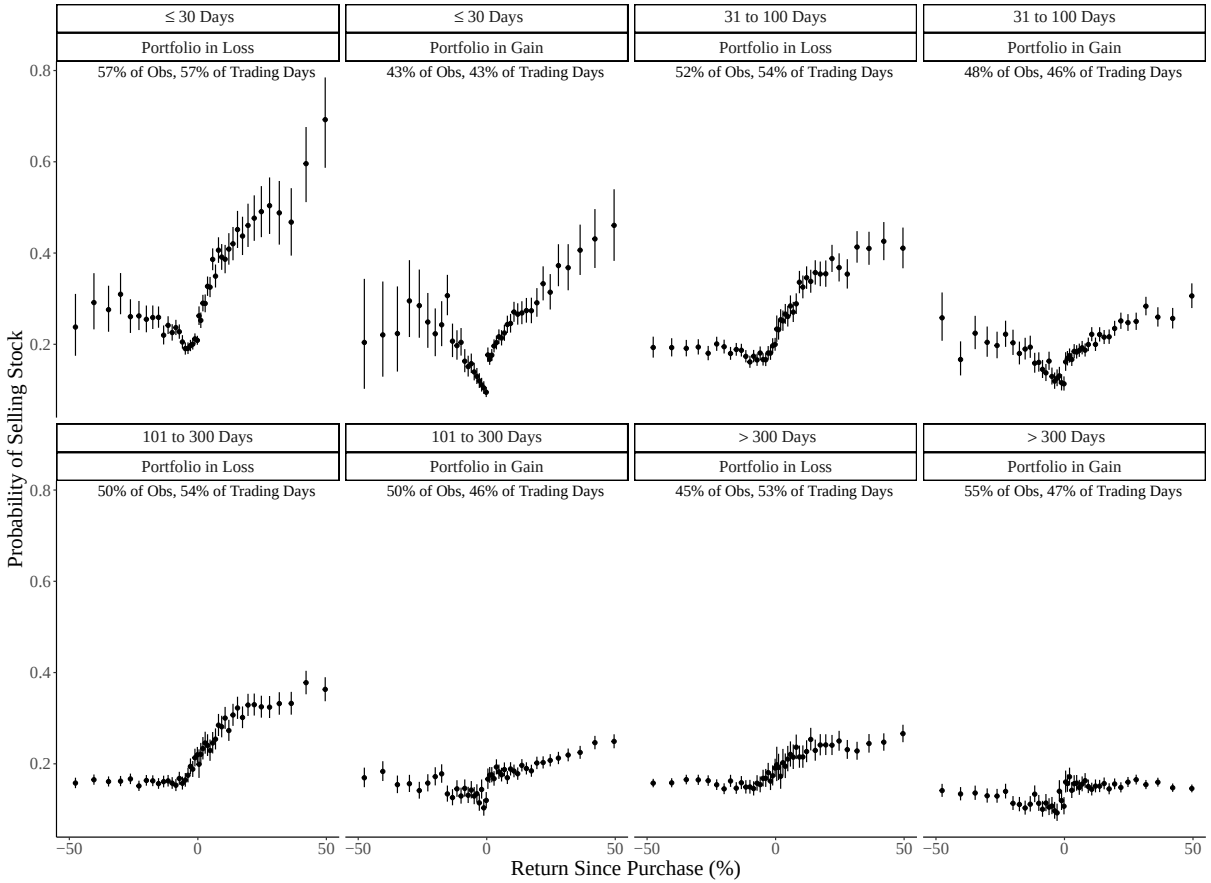
Note: The figure shows the probability of a sale by rank category, portfolio composition, and distinguishing winner from loser stocks. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Blue bars describe the top-two stocks' selling probabilities, while light blue bars, the bottom-two stocks' selling probabilities. Vertical lines represent 95% confidence intervals.

Figure 8: V-Shaped Selling Schedule, LDB Sell-Day Sample



Note: The figure shows binned scatter plots displaying selling probabilities by holding period. The sample includes days in which the investor made at least one sale. Vertical lines represent 95% confidence intervals.

Figure 9: V-Shaped Selling Schedule by Portfolio Performance, LDB Sell-Day Sample



Note: The figure shows binned scatter plots displaying selling probabilities by holding period and portfolio performance. The sample includes days in which the investor made at least one sale. Vertical lines represent 95% confidence intervals.

Table 1: Proportion of Stocks Sold by Rank Category, Barclays Sample

	Login-Day-Sample	Sell-Day-Sample
Rank Group		
All Ranks	0.0081	0.1309
Best	0.0194	0.3441
2nd Best	0.0119	0.2105
Middle	0.0055	0.0846
2nd Worst	0.0068	0.1213
Worst	0.0087	0.1537
Rank Effect		
Best-Middle	0.0139***	0.2595***
	(0.0006)	(0.0079)
Worst-Middle	0.0031***	0.0691***
	(0.0003)	(0.0050)
Observations	5202679	321146

Note: The table presents the ratios of stocks that are sold in the indicated rank category divided by all stocks in that category. For example, the Best row reports #Best Sold/(#Best Sold+#Best Not Sold). Ratios are computed using observations are at the account × stock × day level. Column 1 includes days in which the investor made at least one sale; while Column 2, days in which the investor made at least one login to their account. The last rows present the difference between the indicated groups with standard errors clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table 2: Proportion of Selling Days by Rank Categories, Barclays Sample

Panel (A): Non Mutually Exclusive Rank Categories

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
Any Best Rank	0.4995	0.6362	0.5284	0.4230	0.3967
Any Middle Rank	0.4211	0.3261	0.4335	0.4759	0.4202
Any Worst Rank	0.2453	0.1940	0.2025	0.2679	0.3653
Rank Effect					
Any Best-Any Middle	0.0784***	0.3101***	0.0949***	-0.0529***	-0.0236
	(0.0140)	(0.0225)	(0.0205)	(0.0147)	(0.0179)
Any Worst-Any Middle	-0.1758***	-0.1321***	-0.2310***	-0.2080***	-0.0550***
	(0.0114)	(0.0168)	(0.0161)	(0.0142)	(0.0167)
Observations	30264	6743	9444	9620	4457

Panel (B): Mutually Exclusive Rank Categories

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
Only Best Rank	0.3939	0.5327	0.4193	0.3191	0.2915
Only Middle Rank	0.2950	0.2156	0.3018	0.3467	0.2894
Only Worst Rank	0.1679	0.1201	0.1325	0.1888	0.2701
Rank Effect					
Only Best-Only Middle	0.0989***	0.3171***	0.1175***	-0.0275*	0.0020
	(0.0135)	(0.0221)	(0.0199)	(0.0141)	(0.0167)
Only Worst-Only Middle	-0.1271***	-0.0955***	-0.1693***	-0.1579***	-0.0193
	(0.0101)	(0.0137)	(0.0144)	(0.0130)	(0.0156)
Observations	30264	6743	9444	9620	4457

Note: The table shows rank preferences using data at the account × day level. The sample includes days in which the investor made at least one sale. Panel A shows the proportion of sell days in which the investor sold any stock from the top two positions (*Any Best Rank*), the bottom two positions (*Any Worst Rank*), or positions in between (*Any Middle Rank*). Proportions are not mutually exclusive, i.e., observations from an investor selling a position from the top rank and another from the middle rank will contribute to the computation of proportions for these two rank categories. Column 1 displays proportions for the whole sample. Columns 2 to 5 split the sample by the proportion of stocks in gain in the portfolio. Column 2 includes days in which over 75% of stocks in the portfolio were in loss; likewise, Column 4, days in which over 75% of stocks were in gain. Panel B repeats the same exercise, but proportions are computed including days when the investor sells stocks in only one rank category (i.e., proportions are mutually exclusive). Standard errors in parentheses are clustered by account and date. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 3: Estimates of the Rank Effect, Barclays Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	-0.0366***	-0.0422***	0.0013
	(0.0035)	(0.0035)	(0.0063)
2nd Best	0.0506***	-0.0123*	0.0949***
	(0.0069)	(0.0074)	(0.0103)
Best	0.1880***	0.1162***	0.3007***
	(0.0095)	(0.0088)	(0.0155)
2nd Worst × Proportion of Stocks in Gain			-0.0946***
			(0.0136)
2nd Best × Proportion of Stocks in Gain			-0.2404***
			(0.0207)
Best × Proportion of Stocks in Gain			-0.4116***
			(0.0269)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)		-0.0785***	0.1058***
		(0.0079)	(0.0137)
Number of Stocks (10 stocks)	-0.0436***	-0.0454***	-0.0461***
	(0.0056)	(0.0056)	(0.0057)
Days Since Purchase (100 days)	-0.0166***	-0.0166***	-0.0145***
	(0.0009)	(0.0010)	(0.0009)
Gain Since Purchase=1		0.0773***	0.0817***
		(0.0073)	(0.0078)
Constant	0.2365***	0.2722***	0.1840***
	(0.0071)	(0.0078)	(0.0092)
Observations	121,056	121,056	121,056
R^2	0.0607	0.0632	0.0719

Note: The table presents ordinary least squares regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Estimates of the Rank Effect, Fixed Effects, Barclays Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0014	-0.0274**	-0.0183
	(0.0063)	(0.0129)	(0.0128)
2nd Best	0.0896***	0.1132***	0.1195***
	(0.0104)	(0.0166)	(0.0184)
Best	0.2938***	0.2918***	0.3006***
	(0.0159)	(0.0231)	(0.0244)
2nd Worst × Proportion of Stocks in Gain	-0.0968***	-0.0158	-0.0235
	(0.0135)	(0.0258)	(0.0256)
2nd Best × Proportion of Stocks in Gain	-0.2394***	-0.2242***	-0.2263***
	(0.0207)	(0.0309)	(0.0327)
Best × Proportion of Stocks in Gain	-0.4071***	-0.3657***	-0.3759***
	(0.0267)	(0.0362)	(0.0368)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0913***	0.0752***	0.0555**
	(0.0149)	(0.0207)	(0.0234)
Number of Stocks (10 stocks)	-0.0369***	-0.0493***	-0.0450***
	(0.0089)	(0.0049)	(0.0105)
Days Since Purchase (100 days)	-0.0167***	-0.0095***	-0.0124***
	(0.0011)	(0.0014)	(0.0022)
Gain Since Purchase=1	0.0866***	0.1084***	0.1200***
	(0.0080)	(0.0123)	(0.0130)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	121,056	121,056	121,056
R^2	0.1191	0.8012	0.8356

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Estimates of the Rank Effect
Including Continuous Returns Since Purchase, Barclays Sell-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Rank Effects (Ref: Worst)				
2nd Worst	-0.0120*	-0.0073	-0.0359***	-0.0299**
	(0.0067)	(0.0069)	(0.0131)	(0.0130)
2nd Best	0.0521***	0.0618***	0.0783***	0.0745***
	(0.0124)	(0.0130)	(0.0183)	(0.0207)
Best	0.2613***	0.2679***	0.2632***	0.2626***
	(0.0181)	(0.0187)	(0.0242)	(0.0260)
2nd Worst × Proportion of Stocks in Gain	-0.0891***	-0.0930***	-0.0142	-0.0206
	(0.0135)	(0.0135)	(0.0257)	(0.0255)
2nd Best × Proportion of Stocks in Gain	-0.1899***	-0.2071***	-0.1697***	-0.1604***
	(0.0213)	(0.0212)	(0.0321)	(0.0339)
Best × Proportion of Stocks in Gain	-0.3553***	-0.3717***	-0.2997***	-0.2994***
	(0.0276)	(0.0272)	(0.0368)	(0.0373)
Portfolio/Stock Controls				
Proportion of Stocks in Gain (0-1)	0.0646***	0.0690***	0.0500**	0.0209
	(0.0148)	(0.0160)	(0.0209)	(0.0237)
Number of Stocks (10 stocks)	-0.0415***	-0.0341***	-0.0442***	-0.0406***
	(0.0055)	(0.0085)	(0.0048)	(0.0102)
Days Since Purchase (100 days)	-0.0117***	-0.0151***	-0.0035**	-0.0078***
	(0.0011)	(0.0012)	(0.0016)	(0.0023)
Gain Since Purchase=1	0.0806***	0.0852***	0.1112***	0.1195***
	(0.0082)	(0.0086)	(0.0124)	(0.0132)
Return Since Purchase > 0 (%)	-0.0006***	-0.0003*	-0.0015***	-0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Return Since Purchase < 0 (%)	0.0009***	0.0006***	0.0015***	0.0017***
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
	(0.0276)	(0.0272)	(0.0368)	(0.0373)
Constant	0.2221***			
	(0.0117)			
Account FE	NO	YES	NO	YES
Day × Stock FE	NO	NO	YES	YES
Observations	121,056	121,056	121,056	121,056
R^2	0.0731	0.1194	0.8017	0.8359

Note: The table presents fixed effects regression estimates of the main specification with the addition of continuous control variables for the return since purchase. Two separate variables are added to allow for different slopes for positive and negative returns. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Estimates of the Rank Effect
Including Portfolio and Demographic Controls, Barclays Sell-Day Sample

	$Sale_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank Effects (Ref: Worst)							
2nd Worst	0.0009	0.0009	0.0008	0.0008	0.0008	0.0009	-0.0180
	(0.0064)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0064)	(0.0127)
2nd Best	0.0937***	0.0943***	0.0941***	0.0940***	0.0940***	0.0886***	0.1236***
	(0.0105)	(0.0105)	(0.0106)	(0.0106)	(0.0105)	(0.0106)	(0.0184)
Best	0.3022***	0.3031***	0.3028***	0.3028***	0.3028***	0.2957***	0.3003***
	(0.0158)	(0.0158)	(0.0158)	(0.0158)	(0.0158)	(0.0162)	(0.0241)
2nd Worst × Proportion of Stocks in Gain	-0.0960***	-0.0957***	-0.0957***	-0.0957***	-0.0957***	-0.0979***	-0.0270
	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0138)	(0.0253)
2nd Best × Proportion of Stocks in Gain	-0.2411***	-0.2409***	-0.2406***	-0.2404***	-0.2404***	-0.2393***	-0.2376***
	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0329)
Best × Proportion of Stocks in Gain	-0.4162***	-0.4165***	-0.4161***	-0.4159***	-0.4159***	-0.4113***	-0.3800***
	(0.0273)	(0.0273)	(0.0273)	(0.0273)	(0.0272)	(0.0271)	(0.0364)
Portfolio/Stock Controls							
Proportion of Stocks in Gain (0-1)	0.1044***	0.1074***	0.1066***	0.1063***	0.1063***	0.0958***	0.0650***
	(0.0137)	(0.0137)	(0.0138)	(0.0138)	(0.0137)	(0.0146)	(0.0227)
Number of Stocks (10 stocks)	-0.0444***	-0.0412***	-0.0411***	-0.0413***	-0.0412***	-0.0284***	-0.0341***
	(0.0057)	(0.0058)	(0.0058)	(0.0059)	(0.0059)	(0.0085)	(0.0107)
Days Since Purchase (100 days)	-0.0149***	-0.0147***	-0.0149***	-0.0150***	-0.0150***	-0.0172***	-0.0131***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0022)
Gain Since Purchase=1	0.0823***	0.0816***	0.0816***	0.0816***	0.0815***	0.0865***	0.1222***
	(0.0079)	(0.0079)	(0.0079)	(0.0079)	(0.0079)	(0.0082)	(0.0134)
Portfolio Value (£10000)		-0.0007***	-0.0007***	-0.0007***	-0.0007***	-0.0023***	-0.0027***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0008)
Account Tenure (years)			0.0013	0.0011	0.0012		
			(0.0023)	(0.0023)	(0.0023)		
Female=1				0.0082	0.0083		
				(0.0052)	(0.0052)		
Age (10 years)					-0.0004		
					(0.0014)		
Constant	0.1795***	0.1784***	0.1759***	0.1756***	0.1775***		
	(0.0091)	(0.0090)	(0.0104)	(0.0104)	(0.0127)		
Account FE	NO	NO	NO	NO	NO	YES	YES
Stock FE	NO	NO	NO	NO	NO	NO	YES
Observations	118,640	118,640	118,640	118,640	118,640	118,640	118,640
R^2	0.0730	0.0733	0.0733	0.0734	0.0734	0.1104	0.8360

Note: The table presents ordinary least squares regression estimates of the main specification with the addition of demographic controls and (daily level) portfolio controls. The sample includes days in which the investor made at least one sale. Outliers (investor × stock × days) at the 1st and 99th percentiles of daily portfolio values are excluded. Account tenure, gender and age (calculated from decades of birth) are within individual time invariant. Standard errors are clustered by account and day. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 7: The Rank Effect:
Sub-Sample Analysis, Barclays Sell-Day Sample

	2nd Worst		2nd Best		Best		2nd Worst × Prop. Gains		2nd Best × Prop. Gains		Best × Prop. Gains		Constant	
Gender														
Female	-0.0106	(0.0163)	0.0726***	(0.0251)	0.3565***	(0.0412)	-0.0652*	(0.0379)	-0.1776***	(0.0536)	-0.4631***	(0.0682)	0.2028***	(0.0205)
Male	0.0032	(0.0067)	0.0985***	(0.0110)	0.2918***	(0.0161)	-0.0995***	(0.0143)	-0.2509***	(0.0220)	-0.4036***	(0.0284)	0.1818***	(0.0098)
Age														
Below Median	0.0068	(0.0072)	0.1021***	(0.0113)	0.2970***	(0.0165)	-0.1002***	(0.0161)	-0.2321***	(0.0231)	-0.3831***	(0.0287)	0.1769***	(0.0099)
Above Median	-0.0172	(0.0118)	0.0682***	(0.0239)	0.3089***	(0.0335)	-0.0746***	(0.0238)	-0.2549***	(0.0445)	-0.4893***	(0.0588)	0.2120***	(0.0170)
Account Tenure														
Below Median	-0.0010	(0.0083)	0.0874***	(0.0140)	0.2810***	(0.0191)	-0.0920***	(0.0198)	-0.2503***	(0.0302)	-0.3742***	(0.0368)	0.1957***	(0.0127)
Above Median	0.0023	(0.0098)	0.1016***	(0.0148)	0.3174***	(0.0237)	-0.0934***	(0.0190)	-0.2280***	(0.0264)	-0.4370***	(0.0379)	0.1819***	(0.0107)
Portfolio Value														
Below Median	0.0097	(0.0089)	0.0944***	(0.0133)	0.2995***	(0.0192)	-0.1274***	(0.0194)	-0.2259***	(0.0274)	-0.3609***	(0.0334)	0.2061***	(0.0119)
Above Median	-0.0068	(0.0084)	0.0958***	(0.0139)	0.2989***	(0.0225)	-0.0641***	(0.0179)	-0.2590***	(0.0277)	-0.4595***	(0.0391)	0.1630***	(0.0103)
Number of Stocks														
Below Median	0.0016	(0.0095)	0.0636***	(0.0125)	0.2995***	(0.0190)	-0.1084***	(0.0189)	-0.1758***	(0.0236)	-0.3488***	(0.0308)	0.2898***	(0.0129)
Above Median	0.0034	(0.0073)	0.1357***	(0.0144)	0.3054***	(0.0223)	-0.0885***	(0.0177)	-0.3496***	(0.0305)	-0.5145***	(0.0393)	0.1324***	(0.0110)
FTSE 100 Index														
Return in $t-1>0$	-0.0021	(0.0073)	0.1129***	(0.0129)	0.3311***	(0.0186)	-0.0846***	(0.0160)	-0.2539***	(0.0239)	-0.4328***	(0.0307)	0.1772***	(0.0095)
Return in $t-1<0$	0.0041	(0.0092)	0.0782***	(0.0130)	0.2728***	(0.0187)	-0.1034***	(0.0188)	-0.2280***	(0.0277)	-0.3959***	(0.0334)	0.1896***	(0.0123)
Days Since Purchase														
Below Median	-0.0251**	(0.0112)	0.0340**	(0.0155)	0.2859***	(0.0207)	-0.0930***	(0.0206)	-0.1509***	(0.0286)	-0.3385***	(0.0346)	0.2685***	(0.0134)
Above Median	0.0087	(0.0072)	0.1266***	(0.0118)	0.2542***	(0.0159)	-0.0603***	(0.0177)	-0.2945***	(0.0239)	-0.3897***	(0.0265)	0.1194***	(0.0098)

Note: The table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, covariates include rank categories and their interaction with the portfolio composition. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Estimates of the Rank Effect and the Disposition Effect, Barclays Sell-Day Sample

	$Sale_{ijt}$							
	Controlling for the Interaction of the Disposition Effect with the Portfolio Composition			Specification (3) Omitting Rank Effects	Controlling for the Interaction of the Disposition Effect with a Portfolio Gain Dummy (An et al.' original measure)			Specification (7) Omitting Rank Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank Effects (Ref: Worst)								
2nd Worst	-0.0101	-0.0327**	-0.0292**		-0.0027	-0.0309**	-0.0233*	
	(0.0063)	(0.0128)	(0.0128)		(0.0063)	(0.0129)	(0.0128)	
2nd Best	0.0523***	0.0979***	0.0891***		0.0722***	0.0990***	0.1004***	
	(0.0103)	(0.0168)	(0.0189)		(0.0104)	(0.0164)	(0.0183)	
Best	0.2352***	0.2679***	0.2524***		0.2680***	0.2705***	0.2716***	
	(0.0151)	(0.0238)	(0.0254)		(0.0154)	(0.0229)	(0.0244)	
2nd Worst × Proportion of Stocks in Gain	-0.0584***	0.0025	0.0143		-0.0826***	-0.0027	-0.0045	
	(0.0132)	(0.0259)	(0.0261)		(0.0133)	(0.0258)	(0.0258)	
2nd Best × Proportion of Stocks in Gain	-0.1275***	-0.1696***	-0.1147***		-0.1892***	-0.1784***	-0.1612***	
	(0.0209)	(0.0342)	(0.0369)		(0.0203)	(0.0307)	(0.0329)	
Best × Proportion of Stocks in Gain	-0.2628***	-0.2974***	-0.2358***		-0.3443***	-0.3093***	-0.2965***	
	(0.0263)	(0.0417)	(0.0430)		(0.0256)	(0.0363)	(0.0374)	
Portfolio/Stock Controls								
Proportion of Stocks in Gain (0-1)	0.1188***	0.0873***	0.0822***	0.0159	0.0560***	0.0318	-0.0006	
	(0.0159)	(0.0211)	(0.0238)	(0.0199)	(0.0147)	(0.0230)	(0.0244)	
Gain Since Purchase=1	0.1720***	0.1439***	0.1924***	0.3510***	0.1122***	0.1292***	0.1486***	0.2419***
	(0.0116)	(0.0176)	(0.0183)	(0.0163)	(0.0086)	(0.0130)	(0.0135)	(0.0107)
Gain Since Purchase=1 × Proportion of Stocks in Gain	-0.2013***	-0.0941***	-0.1956***	-0.3577***				
	(0.0201)	(0.0306)	(0.0327)	(0.0270)				
Portfolio Gain=1					0.0338***	0.0383***	0.0557***	0.0535***
					(0.0051)	(0.0079)	(0.0089)	(0.0085)
Gain Since Purchase=1 × Portfolio Gain=1					-0.0604***	-0.0551***	-0.0808***	-0.1404***
					(0.0087)	(0.0117)	(0.0123)	(0.0122)
Number of Stocks (10 stocks)	-0.0407***	-0.0507***	-0.0488***	-0.0541***	-0.0383***	-0.0506***	-0.0462***	-0.0495***
	(0.0099)	(0.0050)	(0.0108)	(0.0110)	(0.0092)	(0.0050)	(0.0105)	(0.0102)
Days Since Purchase (100 days)	-0.0164***	-0.0097***	-0.0123***	-0.0128***	-0.0162***	-0.0094***	-0.0114***	-0.0123***
	(0.0011)	(0.0014)	(0.0022)	(0.0022)	(0.0011)	(0.0014)	(0.0022)	(0.0022)
Account FE	YES	NO	YES	YES	YES	NO	YES	YES
Day × Stock FE	NO	YES	YES	YES	NO	YES	YES	YES
Observations	121,056	121,056	121,056	121,056	121,056	121,056	121,056	121,056
R^2	0.1209	0.8013	0.8358	0.8334	0.1201	0.8014	0.8359	0.8324

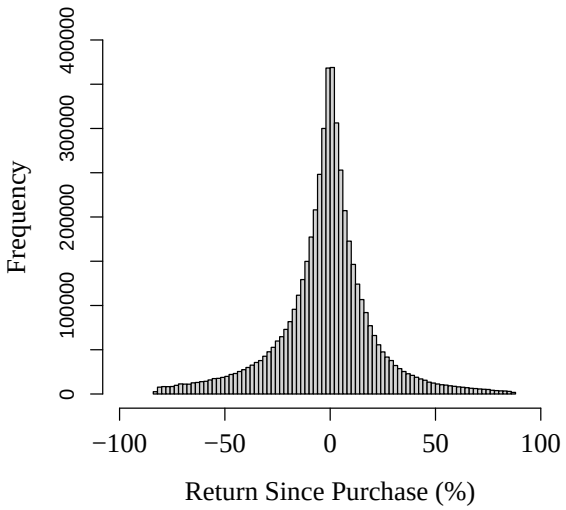
Note: The table presents fixed effects regression estimates of the main specification controlling for the disposition effect and its interaction with the portfolio performance. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Columns 1 to 4 measure portfolio performance as the proportion of stocks in gain in the portfolio. Columns 5 to 8 use An el al.' original measure of portfolio performance, a portfolio gain dummy that takes the value of one if the investor has a net gain in their holdings. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Internet Appendix

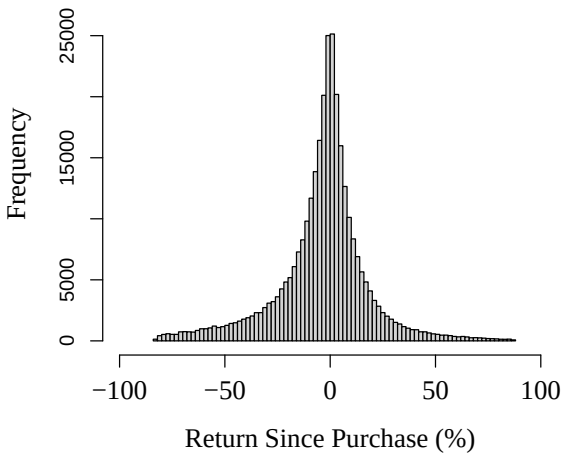
Online Appendix A: Supplementary Items for the Barclays Sample

Figure A1: Histogram of Returns, Barclays Sample

(A) Login-Day Sample

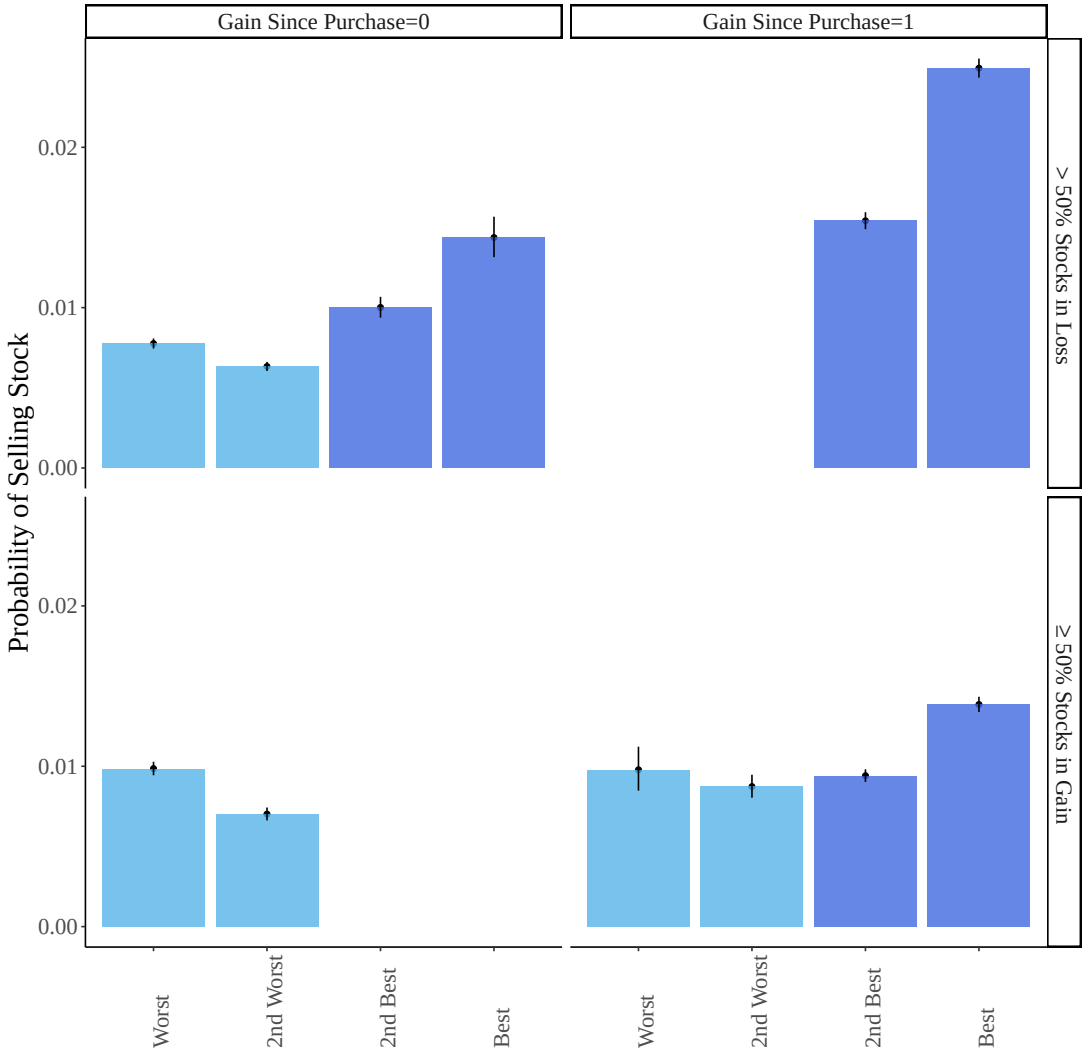


(B) Sell-Day Sample



Note: The figure shows the histograms of returns since purchase. For a better visualization of the distributions, outliers at the 1st and 99th were excluded.

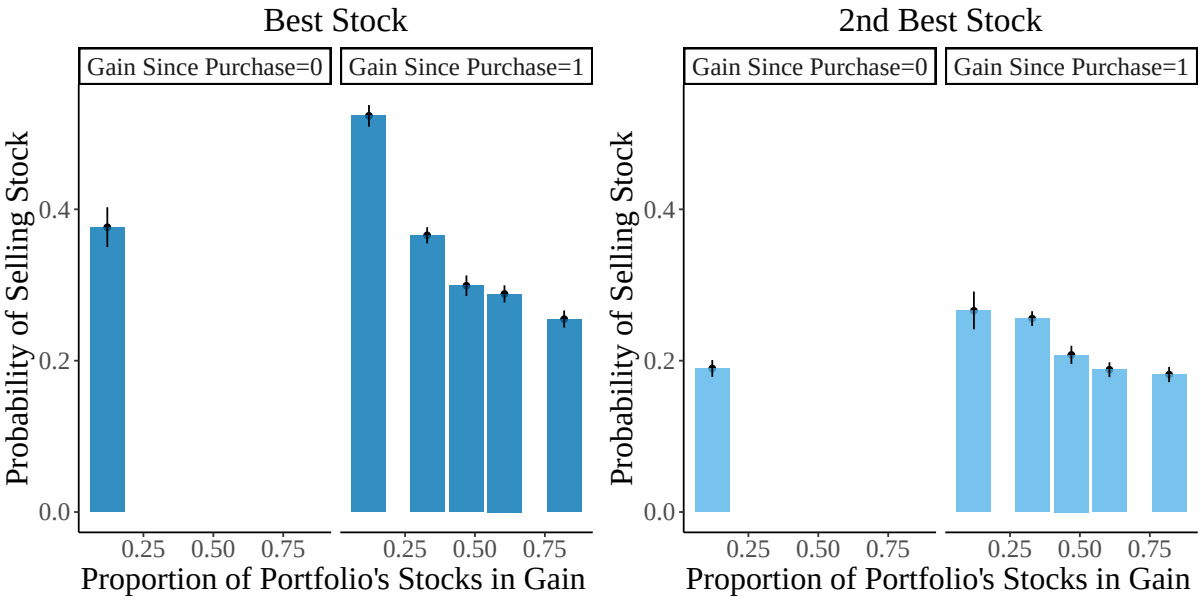
Figure A2: Probability of Selling by Portfolio Compositions and Gain Since Purchase, Barclays Login-Day Sample



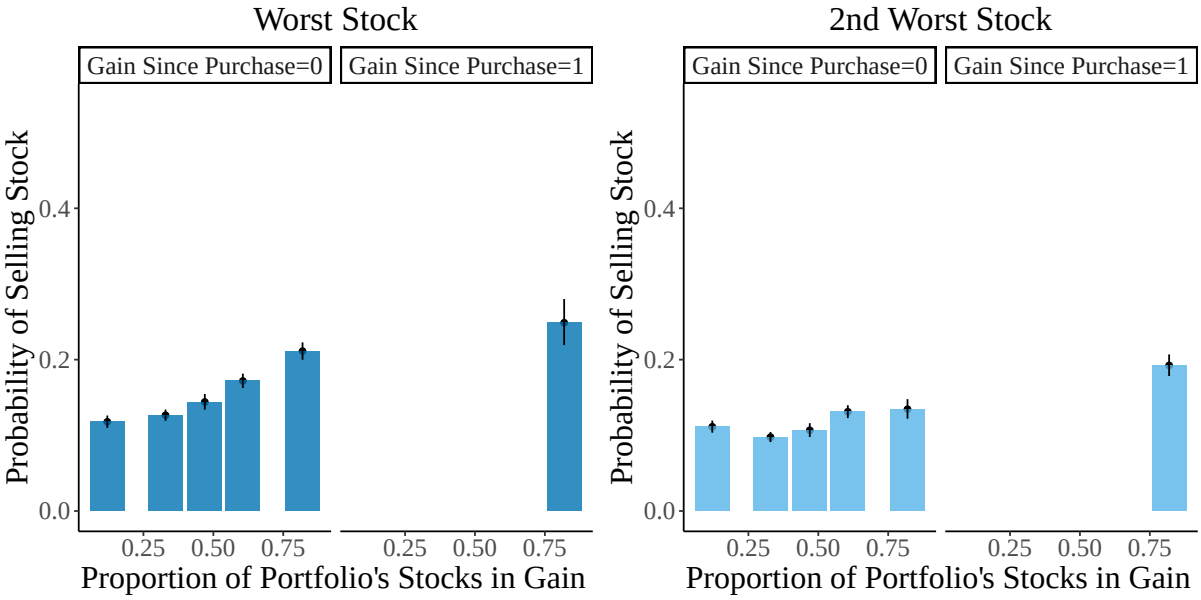
Note: The figure shows the probability of a sale by rank category, portfolio composition, and realized profit. The sample includes days in which the investor made at least one login to their account. Observations are at the account × stock × day level. Blue bars describe the top-two stocks' selling probabilities, while light blue bars, the bottom-two stocks' selling probabilities. Vertical lines represent 95% confidence intervals.

Figure A3: Rank Effects by Portfolio Composition, Barclays Sell-Day Sample

(A) Best Two Positions



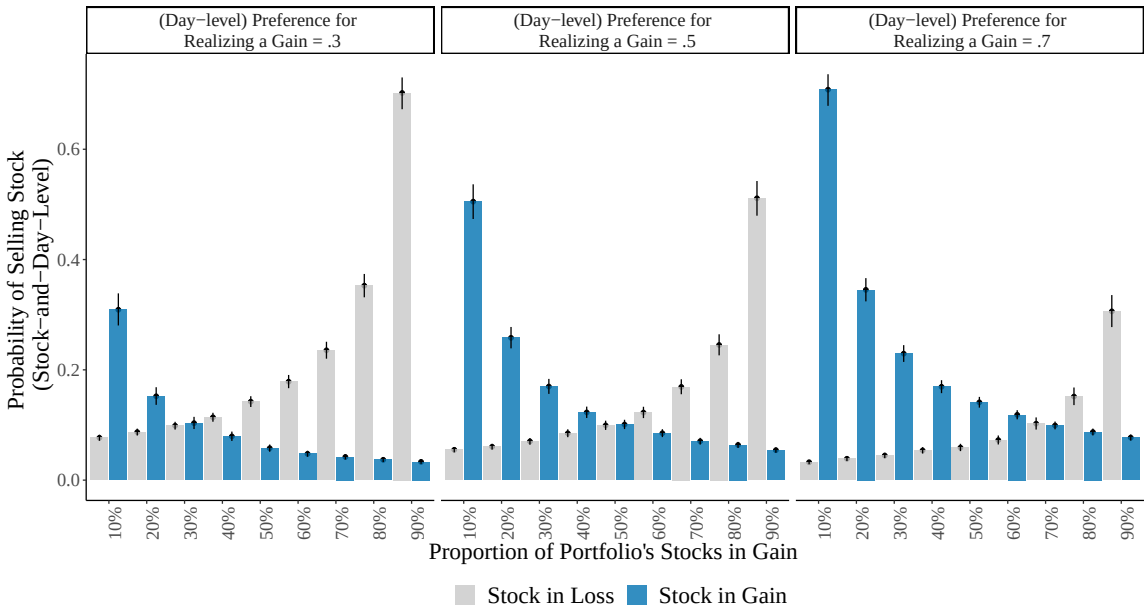
(B) Worst Two Positions



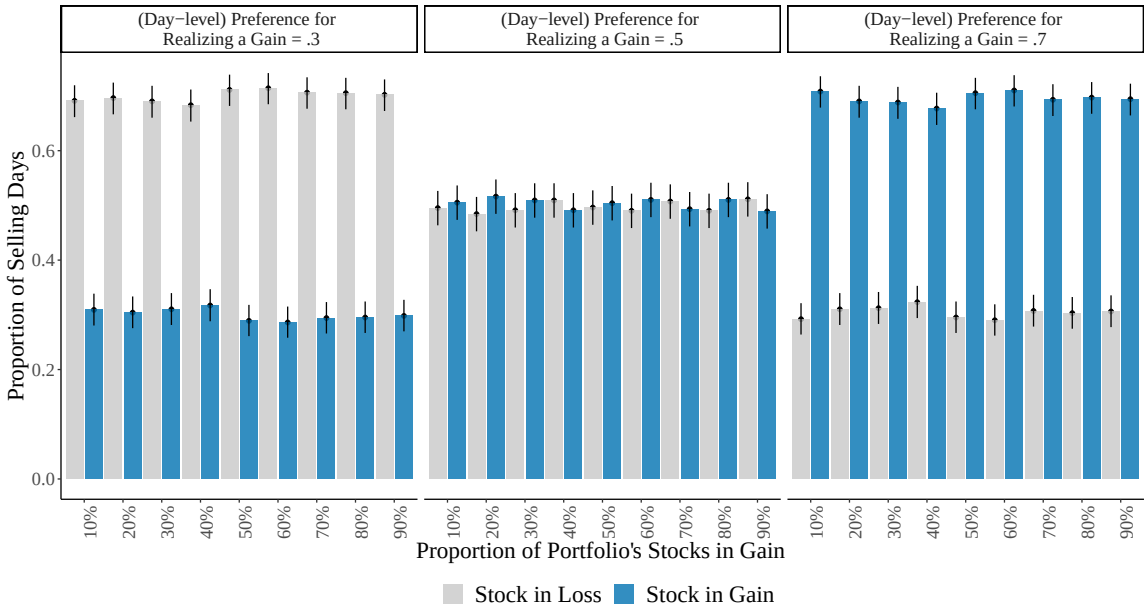
Note: The figure shows the probability of a sale by rank category, quintiles of portfolio performance, and distinguishing winner from loser stocks. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Groups across the x-axis are defined based on quintiles on the proportion of stocks in gain in the portfolio. Panel A describes the top-two stocks' selling probabilities, while Panel B, the bottom-two stocks' selling probabilities. Vertical lines represent 95% confidence intervals.

Figure A4: Simulated Selling Probabilities by Preferences for Realizing Gains

(A) Selling Probability Computed at the Investor × Stock × Day level - Mechanical Interaction with the Portfolio Composition.

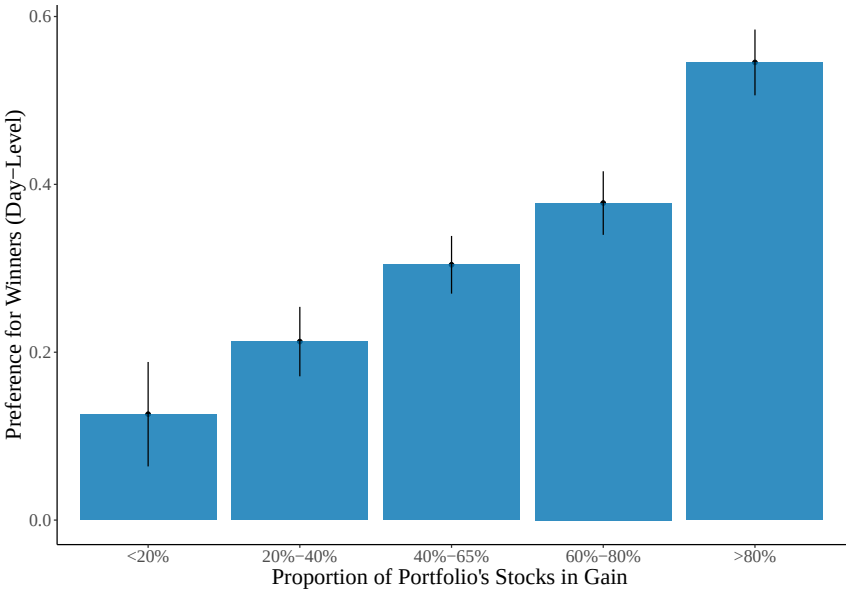


(B) Selling Probability at the Investor × Day level



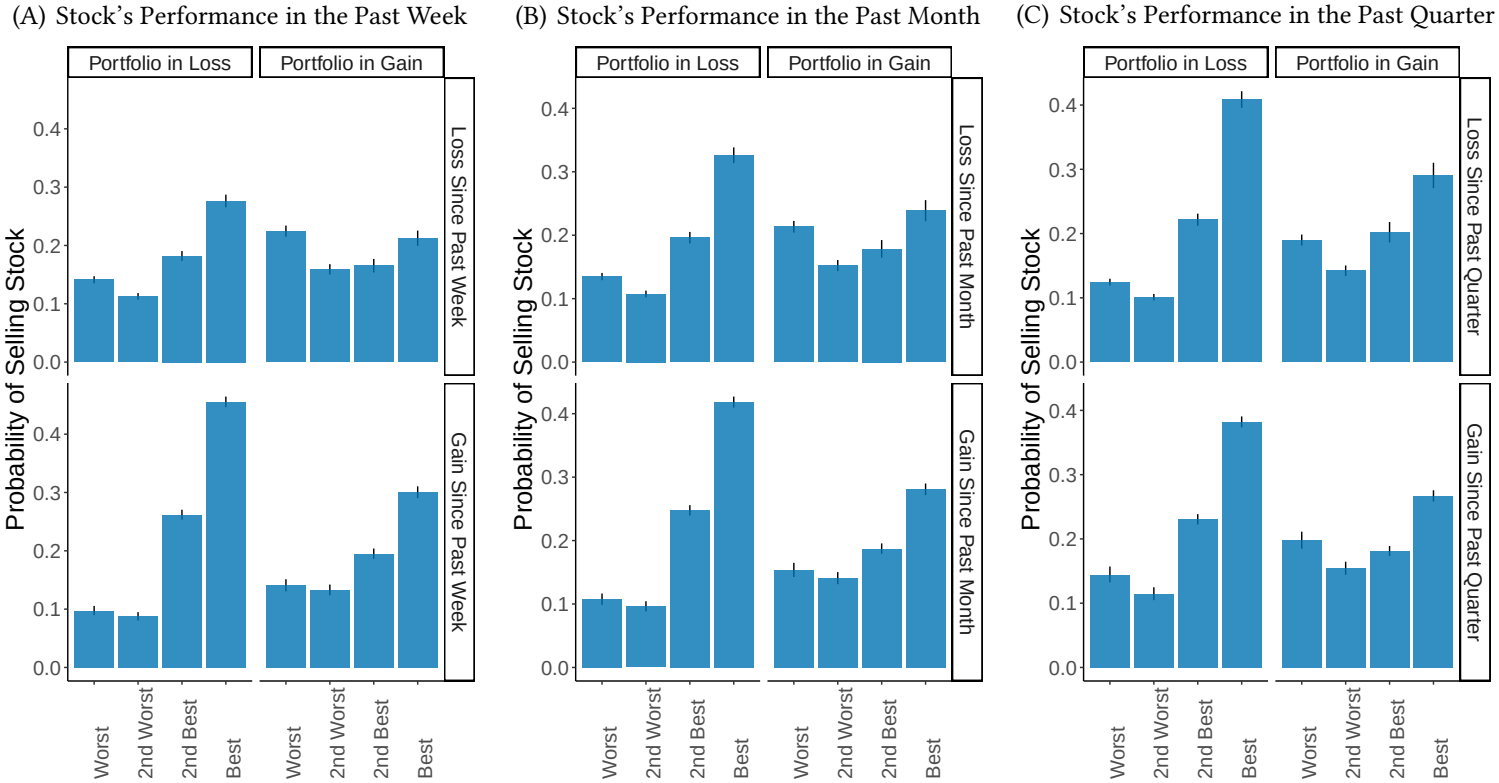
Note: The figure shows the simulated distribution of selling probabilities for 27 different investors that differ in their portfolio composition (from 10% to 90% of stocks in gain) and in their preferences for realizing a gain on the day. For each investor, there are 10,000 observations (1000-days × 10-stocks). Given that empirically retail investors often trade only one stock on each trading day, in the simulated data investors sell only one stock a day, and preferences are defined at the day level (i.e., a gain-loss choice a day). Thus, a preference for realizing a gain of .3 (left panel) implies that on 30% of the selling days, the investor will realize one stock in gain (and on the remaining 70% of the days, one stock in loss). In Panel A, the probability of a sale uses observations at the investor × stock × day level. Blue bars show the probability of realizing a gain; grey bars of realizing a loss. The difference between these two bars represents the disposition effect. Panel B shows the proportion of selling days in which investor realized a stock in gain/loss. Proportions in Panel B use observations at the investor × day level. Vertical lines represent 95% confidence intervals.

Figure A5: Day-Level Preferences for Winners, Barclays Sample



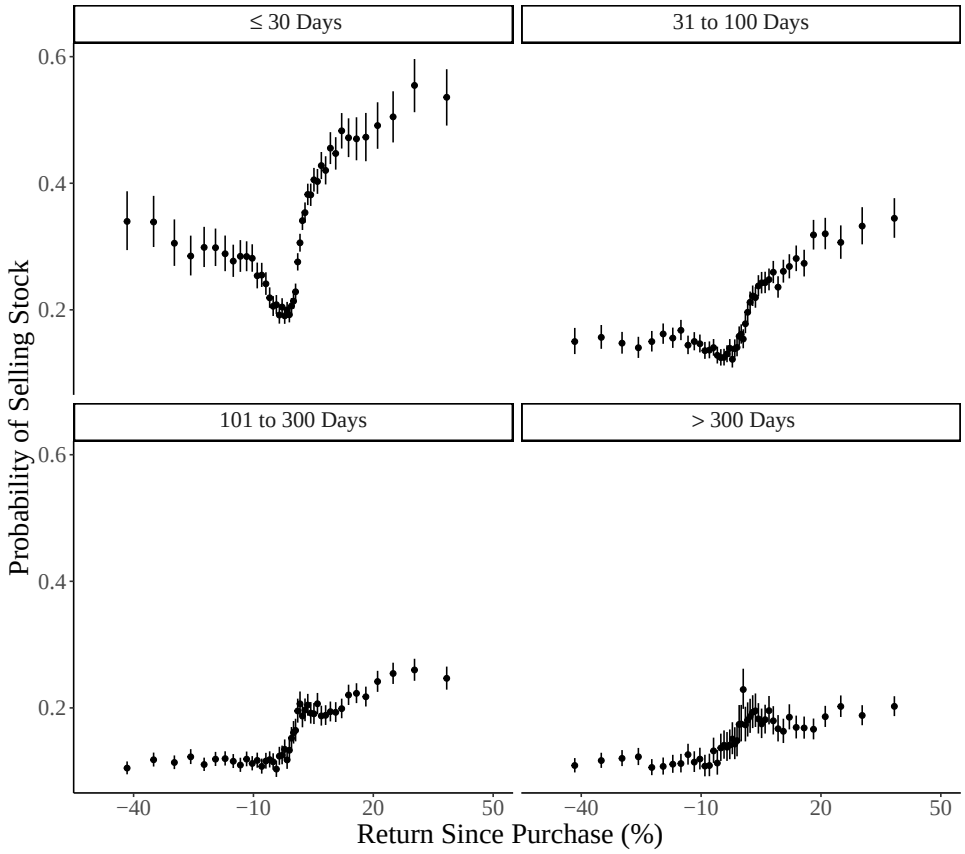
Note: The figure shows the day-level preference for winner stocks by investors' portfolio composition. The sample includes days in which the investor made at least one sale and hold at least one stock in gain and at least one stock in loss. Observations are at the account × day level. The day-level preference for winners is computed as the proportion of selling days in which investors liquidated any winner stocks minus the proportion of days in which they liquidated any loser stock. The plot tests the gain-loss (day level) choice hypothesis (that posits that on each trading day investors first choose whether they want to sell a stock in gain or loss, a gain-loss choice, to then select their preferred stock from the chosen domain). If the hypothesis is correct, the day-level preference for winners should be invariant to fluctuations in the portfolio composition. Vertical lines represent 95% confidence intervals.

Figure A6: Interaction Effect of the Portfolio Performance by Stock' Performance in the Past Week, Month, and Quarter, Barclays Sell-Day Sample



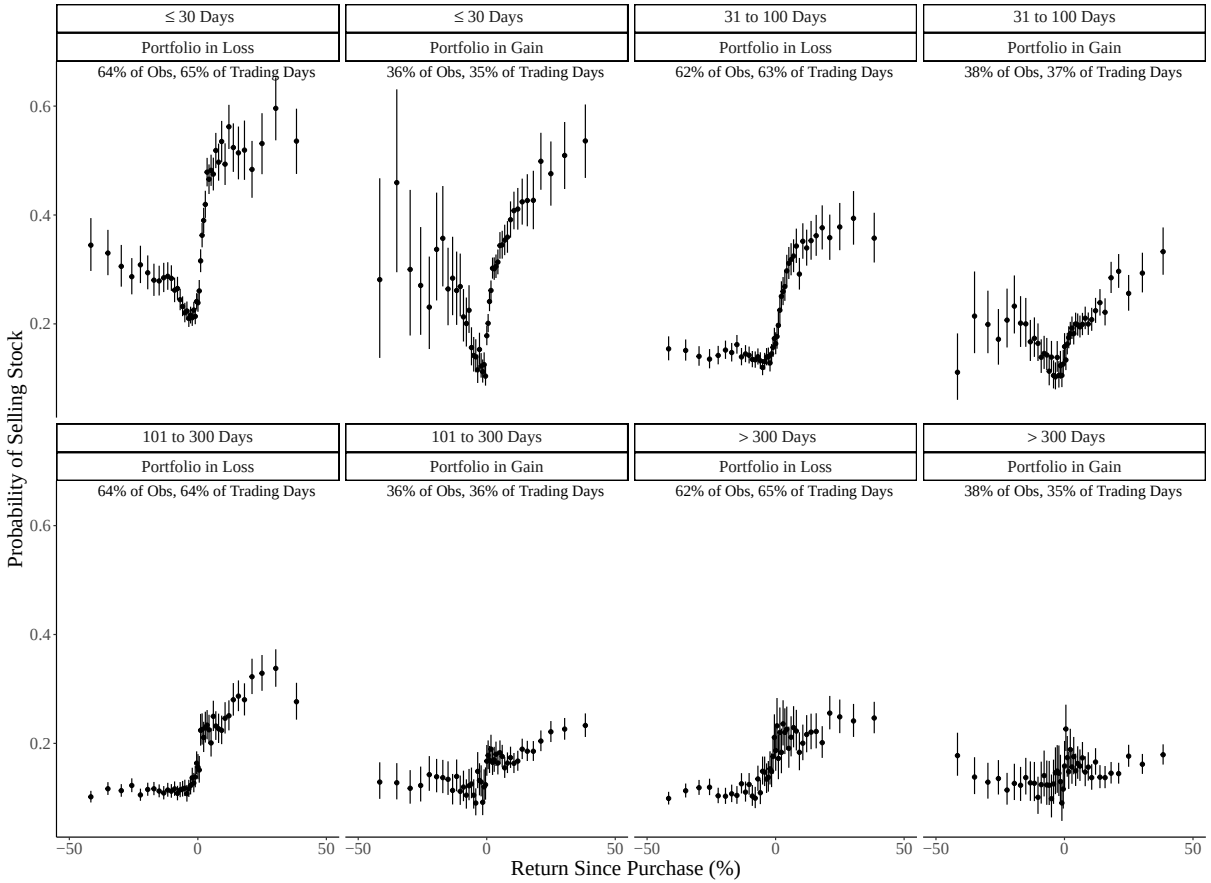
Note: The figure shows the frequency of sales by portfolio size. Panel A displays the average number of stocks sold on a trading day by portfolio size. The sample includes days in which the investor made at least one sale. Panel B shows the probability of a sale using observations at the account × stock × day level. For a better visualization, outliers at the 99th percentile of portfolio size were excluded. Vertical lines represent 95% confidence intervals.

Figure A7: V-Shaped Selling Schedule, Barclays Sell-Day Sample



Note: The figure shows binned scatter plots displaying selling probabilities by holding period. The sample includes days in which the investor made at least one sale. Vertical lines represent 95% confidence intervals.

Figure A8: V-Shaped Selling Schedule by Portfolio Performance, Barclays Sell-Day Sample



Note: The figure shows binned scatter plots displaying selling probabilities by holding period and portfolio performance. The sample includes days in which the investor made at least one sale. Vertical lines represent 95% confidence intervals.

Table A1: Sample Selection in Barclays Dataset

	Accounts	Login-Days	Sells
Starting Sample	13635	12420193	123119
Drop due to:			
Excluding Account × Stocks with Unmatched Prices	21	2276860	13210
Excluding Account × Stocks with Unknown Purchase Price (transfers-in)	1175	2465752	16490
Retaining Account × Stocks × Days with Five Stocks	8339	2474902	51386
Baseline sample	4100	5202679	42033

Note: The table detail the steps in sample selection. Logins-Days in Column 2 reflect the number of observations at the account × stock × day level for the set of days in which the investors made at least one login to their account. Sells in Column 3 include all the stocks' liquidations or partial sells in the data. The largest drop (in step three) restricts the data to portfolios containing at least five stocks. This step also excludes stocks on the day that their position is opened and accounts with missing demographics.

Table A2: Accounts Summary Statistics, Barclays Sample

	Mean	Min	p25	p50	p75	Max
Account Holder Characteristics						
Female	0.152					
Age (years)	50.273	17.000	37.000	47.000	57.000	87.000
Account Characteristics						
Account Tenure (years)	2.299	0.348	1.547	2.297	3.052	3.995
Portfolio Value (£10000)	6.066	0.002	0.640	1.425	3.092	5077.266
Investment in Mutual Funds (£10000)	0.275	0.000	0.000	0.000	0.000	24.980
Investment in Mutual Funds (%)	7.851	0.000	0.000	0.000	0.000	100.000
Number of Stocks	7.820	5.000	5.301	6.401	8.600	57.423
Login days (% all days)	28.975	0.393	11.628	24.884	44.388	71.452
Transaction days (% all market open days)	6.442	0.295	2.357	4.190	7.686	71.667
N Accounts	4100					

Note: The table presents summary statistics for new accounts. Age is measured at 2017. Account tenure is measured on the final day of the data period. Portfolio value is the value of all securities within the portfolio at market prices. Portfolio value and investment in mutual funds are measured as within-account averages of values at the first day of each calendar month in the data period. Number of stocks are measured as within-account averages of the count of stocks during login days. The variable is computed including only the set of days in which the account had at least 5 stocks in their portfolio. Login days is the percentage of days the account is open in the data period and the account holder made at least one login. Transaction days is the percentage of market open days the account is open in the data period and the account holder made at least one trade.

Table A3: Proportion of Stocks Sold by Rank, 5-Stocks-Portfolios, Barclays Sample

	Login-Day-Sample	Sell-Day-Sample
Rank Group		
All Ranks	0.0138	0.2558
Best	0.0235	0.4360
2nd Best	0.0141	0.2608
Middle	0.0104	0.1935
2nd Worst	0.0096	0.1787
Worst	0.0113	0.2098
Rank Effect		
Best-Middle	0.0131***	0.2425***
	(0.0007)	(0.0114)
Worst-Middle	0.0009*	0.0164*
	(0.0005)	(0.0089)
Observations	521800	28120

Note: The table presents the ratios of stocks that are sold in the indicated rank category divided by all stocks in that category. The table is restricted to portfolios composed by five stocks. For example, the Best row reports #Best Sold/(#Best Sold+#Best Not Sold). Ratios are computed using observations are at the account × stock × day level. Column 1 includes days in which the investor made at least one sale; while Column 2, days in which the investor made at least one login to their account. The last rows present the difference between the indicated groups with standard errors clustered by account and date. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A4: Proportion of Stocks Sold by Rank Categories and Investors' Portfolio Composition, Barclays Sell-Day Sample

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
All Ranks	0.2074	0.2276	0.2038	0.1937	0.2139
Best	0.3441	0.4775	0.3478	0.2826	0.2670
2nd Best	0.2105	0.2107	0.2391	0.1941	0.1849
2nd Worst	0.1213	0.1066	0.1005	0.1277	0.1737
Worst	0.1537	0.1154	0.1278	0.1706	0.2300
Rank Effect					
Best-Worst	0.1904***	0.3622***	0.2200***	0.1121***	0.0370***
	(0.0098)	(0.0162)	(0.0112)	(0.0107)	(0.0134)
Observations	121056	26972	37776	38480	17828

Note: The table presents the ratios of stocks that are sold in the indicated rank category by the investor's portfolio composition. Column 1 includes all portfolios. Columns 2-5 split the data by the proportion of stocks in gain in the portfolios. Ratios are computed using observations at the account × stock × day level. The sample includes days in which the investor made at least one sale. Only the best/worst two stocks are included in the sample. The last rows present the difference between the indicated groups with standard errors clustered by account and date. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A5: Proportion of Stocks Sold by Rank Categories and Investors' Portfolio Composition, Barclays Login-Day Sample

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
All Ranks	0.0117	0.0134	0.0128	0.0106	0.0100
Best	0.0194	0.0281	0.0219	0.0154	0.0125
2nd Best	0.0119	0.0124	0.0150	0.0106	0.0087
2nd Worst	0.0068	0.0063	0.0063	0.0070	0.0081
Worst	0.0087	0.0068	0.0080	0.0093	0.0108
Rank Effect					
Best-Worst	0.0107***	0.0213***	0.0138***	0.0061***	0.0017***
	(0.0007)	(0.0014)	(0.0009)	(0.0006)	(0.0006)
Observations	2146108	458372	600596	706172	380968

Note: The table presents the ratios of stocks that are sold in the indicated rank category by the investor's portfolio composition. Column 1 includes all portfolios. Columns 2-5 split the data by the proportion of stocks in gain in the portfolios. Ratios are computed using observations at the account × stock × day level. The sample includes days in which the investor made at least one login to their account. Only the best/worst two stocks are included in the sample. The last rows present the difference between the indicated groups with standard errors clustered by account and date. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A6: Estimates of the Rank Effect, Barclays Login-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	-0.0023***	-0.0029***	-0.0002
	(0.0002)	(0.0002)	(0.0004)
2nd Best	0.0029***	-0.0030***	0.0027***
	(0.0004)	(0.0005)	(0.0006)
Best	0.0110***	0.0044***	0.0144***
	(0.0006)	(0.0005)	(0.0010)
2nd Worst × Proportion of Stocks in Gain			-0.0058***
			(0.0007)
2nd Best × Proportion of Stocks in Gain			-0.0127***
			(0.0014)
Best × Proportion of Stocks in Gain			-0.0219***
			(0.0019)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)		-0.0097***	0.0002
		(0.0011)	(0.0008)
Number of Stocks (10 stocks)	-0.0007	-0.0007*	-0.0007*
	(0.0004)	(0.0004)	(0.0004)
Days Since Purchase (100 days)	-0.0021***	-0.0022***	-0.0021***
	(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1		0.0075***	0.0079***
		(0.0007)	(0.0008)
Constant	0.0151***	0.0196***	0.0147***
	(0.0006)	(0.0007)	(0.0007)
Observations	2,146,108	2,146,108	2,146,108
R^2	0.0045	0.0049	0.0053

Note: The table presents ordinary least squares regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one login to their account. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A7: Estimates of the Rank Effect, Fixed Effects, Barclays Login-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0003	0.0003	0.0005
	(0.0003)	(0.0005)	(0.0005)
2nd Best	0.0043***	0.0070***	0.0077***
	(0.0007)	(0.0010)	(0.0009)
Best	0.0155***	0.0171***	0.0174***
	(0.0010)	(0.0014)	(0.0013)
2nd Worst × Proportion of Stocks in Gain	-0.0061***	-0.0038***	-0.0040***
	(0.0007)	(0.0009)	(0.0009)
2nd Best × Proportion of Stocks in Gain	-0.0162***	-0.0152***	-0.0180***
	(0.0014)	(0.0017)	(0.0016)
Best × Proportion of Stocks in Gain	-0.0254***	-0.0239***	-0.0266***
	(0.0019)	(0.0022)	(0.0021)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0146***	0.0061***	0.0178***
	(0.0013)	(0.0011)	(0.0014)
Number of Stocks (10 stocks)	0.0025***	-0.0015***	0.0007
	(0.0006)	(0.0004)	(0.0006)
Days Since Purchase (100 days)	-0.0005***	-0.0021***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1	0.0083***	0.0109***	0.0116***
	(0.0008)	(0.0009)	(0.0009)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	2,146,108	2,146,108	2,146,108
R^2	0.0337	0.3183	0.3386

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one login to their account. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A8: The Rank Effect:
Sub-Sample Analysis, Barclays Login-Day Sample

	2nd Worst		2nd Best		Best		2nd Worst × Prop. Gains		2nd Best × Prop. Gains		Best × Prop. Gains		Constant	
Gender														
Female	-0.0004	(0.0008)	0.0006	(0.0014)	0.0145***	(0.0023)	-0.0046***	(0.0018)	-0.0091***	(0.0031)	-0.0217***	(0.0042)	0.0128***	(0.0015)
Male	-0.0002	(0.0004)	0.0031***	(0.0007)	0.0144***	(0.0011)	-0.0060***	(0.0008)	-0.0133***	(0.0015)	-0.0220***	(0.0021)	0.0150***	(0.0007)
Age														
Below Median	0.0001	(0.0004)	0.0034***	(0.0007)	0.0151***	(0.0011)	-0.0063***	(0.0009)	-0.0131***	(0.0016)	-0.0218***	(0.0020)	0.0152***	(0.0008)
Above Median	-0.0009	(0.0006)	0.0009	(0.0013)	0.0125***	(0.0022)	-0.0044***	(0.0011)	-0.0111***	(0.0026)	-0.0216***	(0.0041)	0.0130***	(0.0012)
Account Tenure														
Below Median	0.0000	(0.0005)	0.0029***	(0.0009)	0.0144***	(0.0013)	-0.0073***	(0.0011)	-0.0167***	(0.0022)	-0.0235***	(0.0029)	0.0166***	(0.0010)
Above Median	-0.0004	(0.0005)	0.0021**	(0.0009)	0.0133***	(0.0014)	-0.0045***	(0.0010)	-0.0090***	(0.0015)	-0.0193***	(0.0024)	0.0139***	(0.0009)
Portfolio Value														
Below Median	0.0002	(0.0005)	0.0027***	(0.0008)	0.0137***	(0.0012)	-0.0081***	(0.0010)	-0.0126***	(0.0017)	-0.0187***	(0.0021)	0.0154***	(0.0011)
Above Median	-0.0006	(0.0005)	0.0028***	(0.0009)	0.0152***	(0.0016)	-0.0037***	(0.0010)	-0.0127***	(0.0019)	-0.0249***	(0.0029)	0.0133***	(0.0009)
Number of Stocks														
Below Median	-0.0004	(0.0004)	0.0007	(0.0006)	0.0120***	(0.0010)	-0.0060***	(0.0009)	-0.0074***	(0.0012)	-0.0143***	(0.0016)	0.0235***	(0.0013)
Above Median	-0.0000	(0.0005)	0.0064***	(0.0014)	0.0193***	(0.0022)	-0.0055***	(0.0011)	-0.0220***	(0.0027)	-0.0355***	(0.0039)	0.0136***	(0.0011)
FTSE 100 Index														
Return in $t-1>0$	-0.0004	(0.0004)	0.0038***	(0.0008)	0.0167***	(0.0012)	-0.0054***	(0.0008)	-0.0137***	(0.0016)	-0.0239***	(0.0022)	0.0149***	(0.0007)
Return in $t-1<0$	-0.0000	(0.0005)	0.0017**	(0.0007)	0.0125***	(0.0011)	-0.0063***	(0.0010)	-0.0121***	(0.0017)	-0.0207***	(0.0021)	0.0146***	(0.0009)
Days Since Purchase														
Below Median	-0.0018***	(0.0006)	-0.0017	(0.0010)	0.0160***	(0.0016)	-0.0068***	(0.0011)	-0.0084***	(0.0021)	-0.0204***	(0.0029)	0.0250***	(0.0013)
Above Median	0.0004	(0.0004)	0.0039***	(0.0006)	0.0083***	(0.0007)	-0.0030***	(0.0008)	-0.0111***	(0.0011)	-0.0139***	(0.0012)	0.0069***	(0.0005)

Note: The table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, covariates include rank categories and their interaction with the portfolio composition. The sample includes days in which the investor made at least one login to their account. Standard errors are clustered by account and day. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A9: Estimates of the Rank Effect and the Disposition Effect, Barclays Login-Day Sample

	$Sale_{ijt}$							
	Controlling for the Interaction of the Disposition Effect with the Portfolio Composition			Specification (3) Omitting Rank Effects	Controlling for the Interaction of the Disposition Effect with a Portfolio Gain Dummy (An et al.' original measure)			Specification (7) Omitting Rank Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank Effects (Ref: Worst)								
2nd Worst	-0.0014***	-0.0007	-0.0012**		-0.0003	-0.0000	-0.0001	
	(0.0004)	(0.0005)	(0.0005)		(0.0003)	(0.0005)	(0.0005)	
2nd Best	-0.0010*	0.0043***	0.0030***		0.0021***	0.0058***	0.0058***	
	(0.0006)	(0.0010)	(0.0008)		(0.0006)	(0.0010)	(0.0009)	
Best	0.0068***	0.0126***	0.0096***		0.0121***	0.0150***	0.0143***	
	(0.0008)	(0.0013)	(0.0011)		(0.0009)	(0.0013)	(0.0011)	
2nd Worst × Proportion of Stocks in Gain	-0.0003	-0.0003	0.0019**		-0.0042***	-0.0024***	-0.0020**	
	(0.0007)	(0.0008)	(0.0009)		(0.0007)	(0.0008)	(0.0008)	
2nd Best × Proportion of Stocks in Gain	-0.0006	-0.0056***	-0.0022		-0.0099***	-0.0108***	-0.0117***	
	(0.0011)	(0.0015)	(0.0013)		(0.0012)	(0.0015)	(0.0014)	
Best × Proportion of Stocks in Gain	-0.0049***	-0.0116***	-0.0062***		-0.0174***	-0.0183***	-0.0186***	
	(0.0013)	(0.0019)	(0.0016)		(0.0016)	(0.0020)	(0.0018)	
Portfolio/Stock Controls								
Proportion of Stocks in Gain (0-1)	0.0204***	0.0096***	0.0243***	0.0221***	0.0106***	0.0026**	0.0130***	
	(0.0016)	(0.0012)	(0.0016)	(0.0015)	(0.0012)	(0.0011)	(0.0013)	
Gain Since Purchase=1	0.0230***	0.0193***	0.0260***	0.0315***	0.0123***	0.0137***	0.0158***	0.0201***
	(0.0016)	(0.0014)	(0.0017)	(0.0019)	(0.0010)	(0.0011)	(0.0011)	(0.0012)
Gain Since Purchase=1 × Proportion of Stocks in Gain	-0.0326***	-0.0202***	-0.0339***	-0.0383***				
	(0.0024)	(0.0017)	(0.0024)	(0.0025)				
Portfolio Gain=1					0.0044***	0.0037***	0.0056***	0.0079***
					(0.0005)	(0.0004)	(0.0005)	(0.0005)
Gain Since Purchase=1 × Portfolio Gain=1					-0.0087***	-0.0067***	-0.0099***	-0.0132***
					(0.0008)	(0.0007)	(0.0008)	(0.0010)
Number of Stocks (10 stocks)	0.0016***	-0.0021***	-0.0003	-0.0005	0.0022***	-0.0018***	0.0004	0.0003
	(0.0005)	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0004)	(0.0006)	(0.0006)
Days Since Purchase (100 days)	-0.0004***	-0.0021***	-0.0007***	-0.0007***	-0.0004***	-0.0021***	-0.0006***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Account FE	YES	NO	YES	YES	YES	NO	YES	YES
Day × Stock FE	NO	YES	YES	YES	NO	YES	YES	YES
Observations	2,146,108	2,146,108	2,146,108	2,146,108	2,146,108	2,146,108	2,146,108	2,146,108
R^2	0.0345	0.3185	0.3392	0.3389	0.0340	0.3184	0.3389	0.3385

Note: The table presents fixed effects regression estimates of the main specification controlling for the disposition effect and its interaction with the portfolio performance. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Columns 1 to 3 measure portfolio performance as the proportion of stocks in gain in the portfolio. Columns 3 to 6 use An el al.' original measure of portfolio performance, a portfolio gain dummy that takes the value of one if the investor has a net gain in their holdings. The sample includes days in which the investor made at least one login to their account. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A10: Estimates of the Rank Effect, Complete Liquidations, Fixed Effects, Barclays Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	-0.0008	-0.0214*	-0.0093
	(0.0054)	(0.0122)	(0.0119)
2nd Best	0.0431***	0.0503***	0.0732***
	(0.0083)	(0.0143)	(0.0165)
Best	0.2132***	0.2190***	0.2446***
	(0.0146)	(0.0203)	(0.0217)
2nd Worst × Proportion of Stocks in Gain	-0.0950***	-0.0433*	-0.0564**
	(0.0120)	(0.0245)	(0.0238)
2nd Best × Proportion of Stocks in Gain	-0.1900***	-0.1746***	-0.1823***
	(0.0185)	(0.0287)	(0.0306)
Best × Proportion of Stocks in Gain	-0.3361***	-0.3129***	-0.3301***
	(0.0251)	(0.0344)	(0.0347)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0690***	0.0590***	0.0720***
	(0.0134)	(0.0193)	(0.0223)
Number of Stocks (10 stocks)	-0.0222***	-0.0404***	-0.0198**
	(0.0054)	(0.0049)	(0.0079)
Days Since Purchase (100 days)	-0.0180***	-0.0152***	-0.0184***
	(0.0010)	(0.0012)	(0.0018)
Gain Since Purchase=1	0.0845***	0.1137***	0.1197***
	(0.0079)	(0.0121)	(0.0123)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	121,056	121,056	121,056
R^2	0.1294	0.7962	0.8366

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock (liquidating the entire position) and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A11: Estimates of the Rank Effect, Complete Liquidations, Fixed Effects, Barclays Login-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0001	0.0001	0.0004
	(0.0003)	(0.0004)	(0.0004)
2nd Best	0.0019***	0.0039***	0.0049***
	(0.0005)	(0.0007)	(0.0007)
Best	0.0113***	0.0128***	0.0135***
	(0.0009)	(0.0011)	(0.0011)
2nd Worst × Proportion of Stocks in Gain	-0.0057***	-0.0040***	-0.0043***
	(0.0006)	(0.0008)	(0.0008)
2nd Best × Proportion of Stocks in Gain	-0.0129***	-0.0120***	-0.0149***
	(0.0012)	(0.0014)	(0.0014)
Best × Proportion of Stocks in Gain	-0.0209***	-0.0196***	-0.0223***
	(0.0017)	(0.0019)	(0.0019)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0114***	0.0045***	0.0148***
	(0.0012)	(0.0009)	(0.0012)
Number of Stocks (10 stocks)	0.0025***	-0.0014***	0.0011**
	(0.0005)	(0.0004)	(0.0005)
Days Since Purchase (100 days)	-0.0005***	-0.0019***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1	0.0075***	0.0101***	0.0110***
	(0.0007)	(0.0009)	(0.0009)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	2,146,108	2,146,108	2,146,108
R^2	0.0302	0.3237	0.3423

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock (liquidating the entire position) and zero otherwise. The sample includes days in which the investor made at least one login to their account. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A12: Estimates of the Rank Effect, Tax-Motivated Selling, Fixed Effects, Barclays Sell-Day Sample

	$Sale_{ijt}$					
	Excluding the Month Prior to the End of the Tax Year			Excluding Tax Liable Accounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Rank Effects (Ref: Worst)						
2nd Worst	0.0011	-0.0308**	-0.0230*	-0.0049	0.0018	0.0063
	(0.0067)	(0.0138)	(0.0137)	(0.0096)	(0.0233)	(0.0244)
2nd Best	0.0851***	0.1033***	0.1082***	0.0603***	0.0712***	0.0998***
	(0.0111)	(0.0177)	(0.0197)	(0.0148)	(0.0259)	(0.0313)
Best	0.2875***	0.2805***	0.2911***	0.2361***	0.2220***	0.2499***
	(0.0166)	(0.0246)	(0.0263)	(0.0238)	(0.0358)	(0.0393)
2nd Worst × Proportion of Stocks in Gain	-0.1009***	-0.0122	-0.0214	-0.0985***	-0.0469	-0.0443
	(0.0144)	(0.0276)	(0.0273)	(0.0203)	(0.0481)	(0.0499)
2nd Best × Proportion of Stocks in Gain	-0.2358***	-0.2113***	-0.2101***	-0.2265***	-0.1423***	-0.1830***
	(0.0222)	(0.0341)	(0.0359)	(0.0280)	(0.0504)	(0.0567)
Best × Proportion of Stocks in Gain	-0.3932***	-0.3467***	-0.3629***	-0.3572***	-0.2795***	-0.3340***
	(0.0279)	(0.0381)	(0.0391)	(0.0384)	(0.0564)	(0.0587)
Portfolio/Stock Controls						
Proportion of Stocks in Gain (0-1)	0.0856***	0.0714***	0.0471*	0.0838***	0.0445	0.0710*
	(0.0160)	(0.0226)	(0.0263)	(0.0200)	(0.0347)	(0.0425)
Number of Stocks (10 stocks)	-0.0383***	-0.0484***	-0.0453***	-0.0319**	-0.0441***	-0.0428***
	(0.0094)	(0.0054)	(0.0114)	(0.0126)	(0.0106)	(0.0161)
Days Since Purchase (100 days)	-0.0171***	-0.0093***	-0.0121***	-0.0168***	-0.0096***	-0.0089***
	(0.0012)	(0.0015)	(0.0023)	(0.0014)	(0.0021)	(0.0032)
Gain Since Purchase=1	0.0863***	0.1102***	0.1181***	0.0866***	0.0986***	0.1038***
	(0.0084)	(0.0133)	(0.0143)	(0.0103)	(0.0207)	(0.0239)
Account FE	YES	NO	YES	YES	NO	YES
Day × Stock FE	NO	YES	YES	NO	YES	YES
Observations	107,304	107,304	107,304	62,584	62,584	62,584
R^2	0.1195	0.8061	0.8423	0.1015	0.8692	0.9025

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Columns 1 to 3 exclude from the sample the month before the end of the tax year (in the UK, the tax year ends on 5 April). Columns 4 to 6 exclude from the sample tax liable accounts. The latter exclusion restricts the analysis to 2249 accounts, which include principally Retail Individual Savings Accounts (ISA) and a small proportion (16%) of accounts are money-purchase Self-Invested Personal Pensions (SIPP). Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table A13: Estimates of the Rank Effect, Tax-Motivated Selling, Fixed Effects, Barclays Login-Day Sample

	$Sale_{ijt}$					
	Excluding the Month Prior to the End of the Tax Year			Excluding Tax Liable Accounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Rank Effects (Ref: Worst)						
2nd Worst	0.0003	0.0003	0.0004	-0.0002	-0.0004	-0.0001
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)
2nd Best	0.0040***	0.0068***	0.0074***	0.0025***	0.0043***	0.0046***
	(0.0007)	(0.0011)	(0.0009)	(0.0008)	(0.0011)	(0.0011)
Best	0.0150***	0.0165***	0.0167***	0.0116***	0.0123***	0.0124***
	(0.0010)	(0.0014)	(0.0013)	(0.0013)	(0.0016)	(0.0015)
2nd Worst × Proportion of Stocks in Gain	-0.0063***	-0.0040***	-0.0041***	-0.0051***	-0.0030**	-0.0035***
	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0013)
2nd Best × Proportion of Stocks in Gain	-0.0160***	-0.0155***	-0.0181***	-0.0131***	-0.0114***	-0.0136***
	(0.0015)	(0.0018)	(0.0017)	(0.0016)	(0.0019)	(0.0019)
Best × Proportion of Stocks in Gain	-0.0247***	-0.0234***	-0.0259***	-0.0204***	-0.0179***	-0.0204***
	(0.0020)	(0.0022)	(0.0022)	(0.0022)	(0.0024)	(0.0024)
Portfolio/Stock Controls						
Proportion of Stocks in Gain (0-1)	0.0144***	0.0058***	0.0179***	0.0108***	0.0041***	0.0142***
	(0.0014)	(0.0012)	(0.0014)	(0.0016)	(0.0013)	(0.0017)
Number of Stocks (10 stocks)	0.0023***	-0.0015***	0.0005	0.0019***	-0.0014**	0.0006
	(0.0006)	(0.0004)	(0.0006)	(0.0007)	(0.0006)	(0.0007)
Days Since Purchase (100 days)	-0.0004***	-0.0020***	-0.0007***	-0.0004***	-0.0019***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1	0.0083***	0.0109***	0.0116***	0.0068***	0.0093***	0.0101***
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Account FE	YES	NO	YES	YES	NO	YES
Day × Stock FE	NO	YES	YES	NO	YES	YES
Observations	1,924,532	1,924,532	1,924,532	1,234,872	1,234,872	1,234,872
R^2	0.0346	0.3217	0.3429	0.0307	0.4080	0.4249

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one login to their account. Columns 1 to 3 exclude from the sample the month before the end of the tax year (in the UK, the tax year ends on 5 April). Columns 4 to 6 exclude from the sample tax liable accounts. The latter exclusion restricts the analysis to 2249 accounts, which include principally Retail Individual Savings Accounts (ISA) and a small proportion (16%) of accounts are money-purchase Self-Invested Personal Pensions (SIPP). Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Online Appendix B: Supplementary Items for the LDB Sample

Additional Results

Replication of Table 5 in Hartzmark (2015)

Hartzmark (2015) presents estimates from samples that restrict the data to individual investor portfolios for which all positions are either at a gain or at a loss. A copy of Table 5 in his paper is shown in Table B5. The table displays marginal effects from logit regressions of a dummy variable equal to one if a stock is sold on characteristics of the stock being held. Each column includes rank variables and additional controls ($Return$, $Return * \sqrt[2]{HoldingDays}$, $Variance$, and $\sqrt[2]{HoldingDays}$).

In Table B6, I provide a reestimation of Table 5 in Hartzmark (2015). The table presents ordinary least squares regression estimates to enable comparison with results from additional tests on the raw data described in detail below.[32] Columns 1 and 3 feature sub-samples where all securities in investors' portfolios are at a gain or at a loss, respectively. Column 2 includes portfolios with a mixture of stocks in gain and stocks in loss. Each specification includes the same set of controls used in Table B5.

Before discussing the rank effect estimates across these tables, it is important to note some differences in the sample sizes. The baseline LDB sample used here considers 7,083 accounts, a smaller number of accounts than the sample used in Hartzmark (2015) of 10,619 accounts. Detailed steps in sample selection are shown in Table B1. While Hartzmark (2015) and I follow several of the cleaning steps described in Ben-David and Hirshleifer (2012), this paper includes additional steps that guarantee an accurate computation of the portfolio performance. More specifically, we both drop portfolios containing positions for which the purchase price is unknown. Hartzmark (2015) accomplishes this by excluding accounts present in the first month of the position files—the LDB raw data comprise a set of files with monthly position information and an additional file with daily trading activity. In addition to this step, I also drop accounts for which the position files reveal that the account has held stocks before the first transaction registered in the file of trading activity. Because these accounts contain stocks with unknown purchase prices, excluding them guarantees an accurate computation of the proportion of stocks in gain in the portfolio as well as of the stocks' ranks. As detailed in Table B1, this additional step drops nearly 8,000 accounts.

Moving now on to discussing rank effect estimates, I make three observations about the results displayed in Table B6 and Table B5. First, both tables pool portfolios of different sizes together, and so they both present inflated rank effect estimates. Second, even though Table B6 shows the expected larger gap between the Best-Worst coefficients for All-Loss portfolios (Column 3) relative to All-Gain portfolios (Column 1), any comparison of coefficients across columns is generally hardly uninformative without much precision on the average number of stocks held in each sub-sample. Because smaller portfolios have much lower selling probabilities than larger portfolios when the data is structured at the account × stock × day level, large coefficients do not necessarily imply larger effects. For instance, All-Gain portfolios and All-Loss portfolios are likely to contain fewer stocks than Mix portfolios. Third, setting aside these caveats, we can note in Column 2 of Table B5 (from Hartzmark, 2015) a slightly smaller coefficient for the best stock (relative to the worst stock), together with an exceptionally large positive coefficient for the return since purchase (albeit imprecise). These observations suggest potential multicollinearity between the dummy for the best stock and the control for return

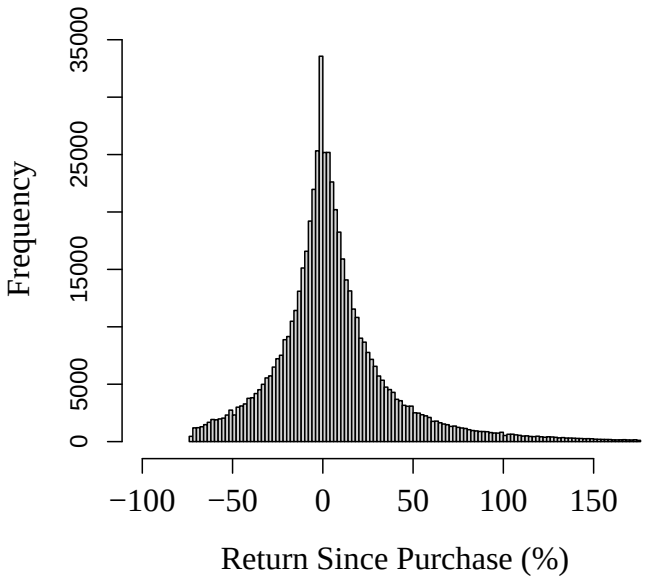
[32] However, a similar pattern of results is obtained from logit regressions.

since purchase. To prevent the overinterpretation of Table B6 and Table B5, I discuss next additional sub-samples analyses of the data that address the concerns raised above.

In Table B7, I split the sub-samples of All-Gain, All-Loss, and Mix portfolios into sets of portfolios containing an equal number of stocks.[33] Column 1 includes all portfolios; Columns 2 to 5 restrict the sample to portfolios holding 5, 7, 9 and 11 stocks, respectively. The table presents unconditional selling probabilities for each rank category. Under the asymmetric rank hypothesis, we should expect a larger Best-Worst gap for All-Loss portfolios than All-Gain portfolios. This is precisely what we observe in the data. In Column 2, the Best-Worst gap is nearly seven percentage points for All-Loss portfolios, but only three percentage points for All-Gain portfolios. These differences are more prominent in Columns 3 to 5. This set of evidence is consistent with all empirical results discussed in the paper.

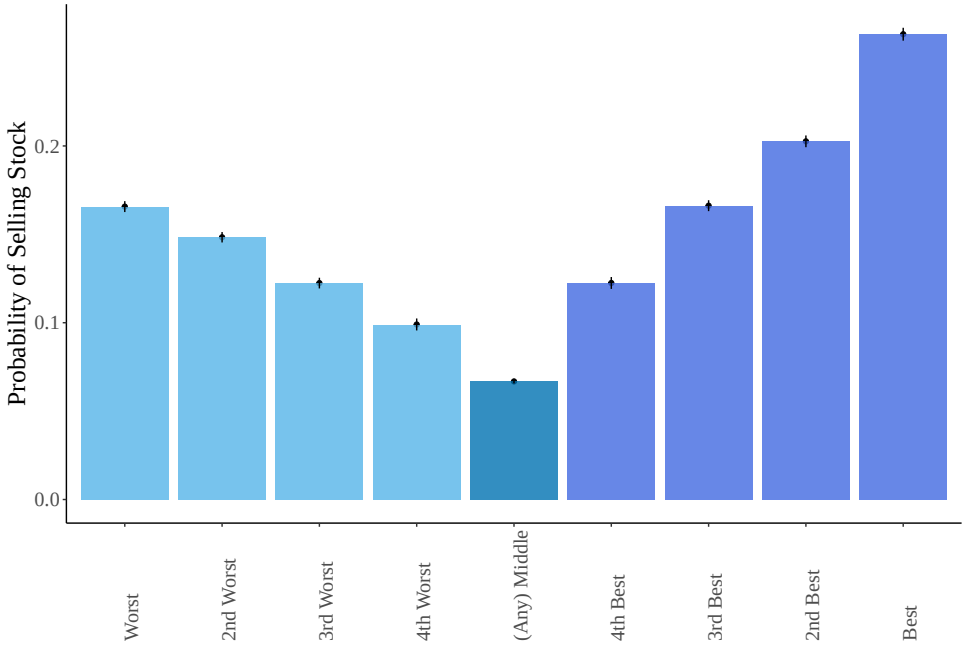
[33] The number of observations in Table B7 is slightly smaller than in Table B6 because Table B7 includes controls for the variance of stocks' returns over the previous year (calculated using the previous 250 days' daily returns, if there are at least fifty non-missing observations); therefore, observations without stocks' variance are omitted.

Figure B1: Histogram of Returns, LDB Sample



Note: The figure shows the histograms of returns since purchase. For a better visualization of the distributions, outliers at the 1st and 99th percentiles were excluded.

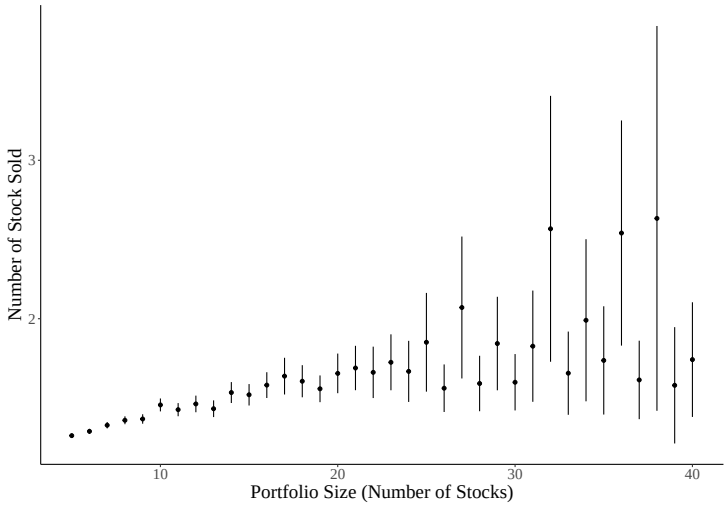
Figure B2: Unconditional Rank Effect, LDB Sell-Day Sample



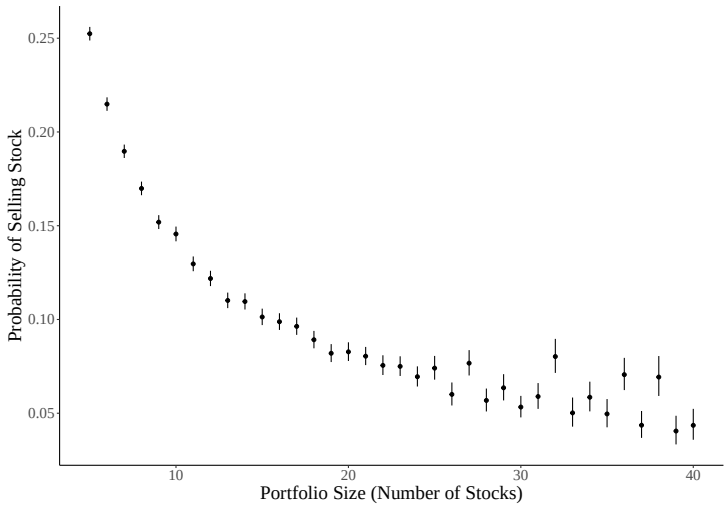
Note: The figure shows the unconditional probability of a sale based on rank positions. Observations are at the account × stock × day level. The sample includes days in which the investor made at least one sale. Each bar represents the ratio of stocks that are sold in the indicated category divided by all stocks in that category. For example, the *Worst* bar reports #Worst Sold/(#Worst Sold + #Worst Not Sold). Vertical lines represent 95% confidence intervals.

Figure B3: Number of Stocks Sold on a Trading Day by Portfolio Size, LDB Sample

(A) Numbers of Stocks Sold on a Trading Day

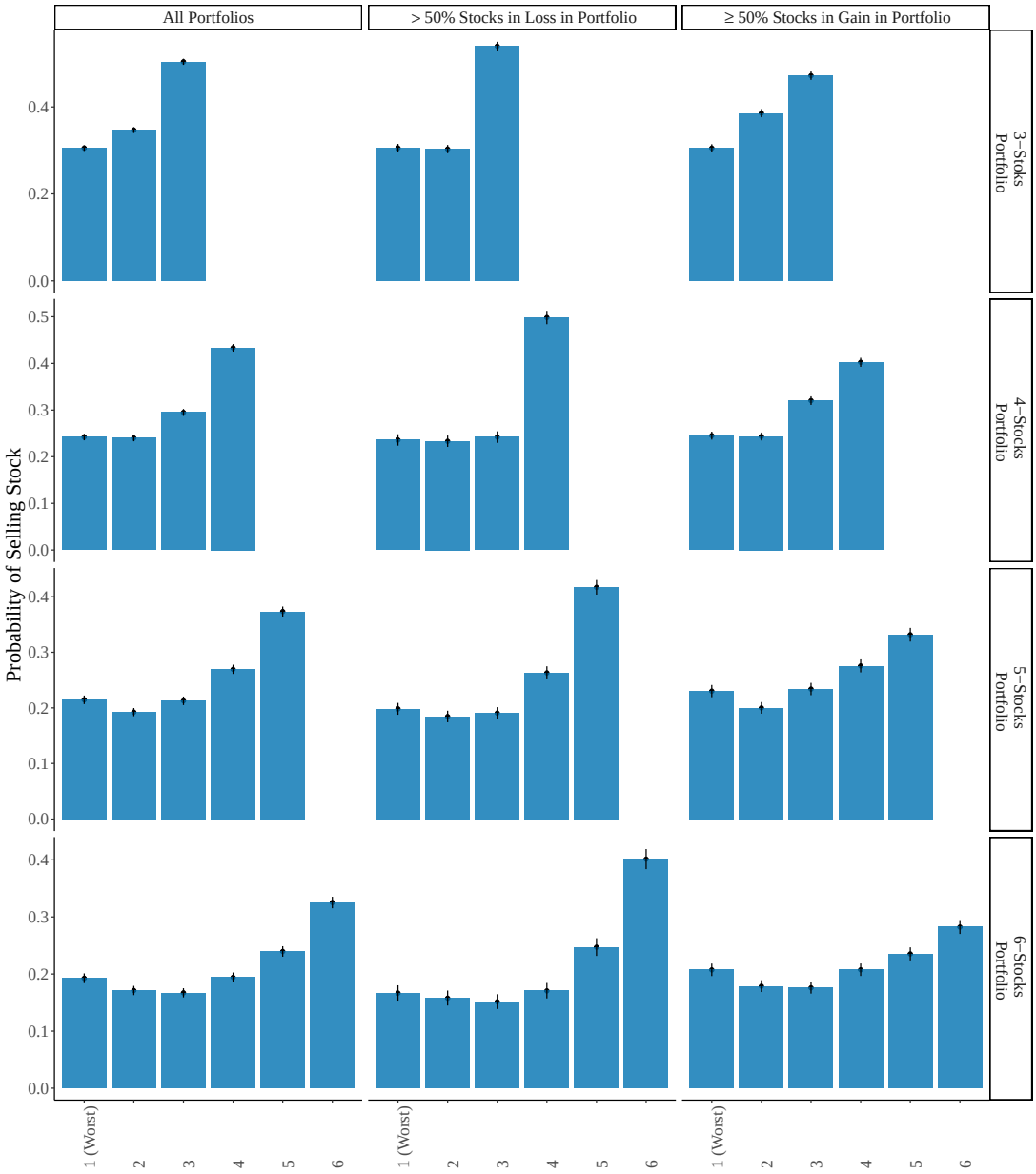


(B) Probability of a Sale



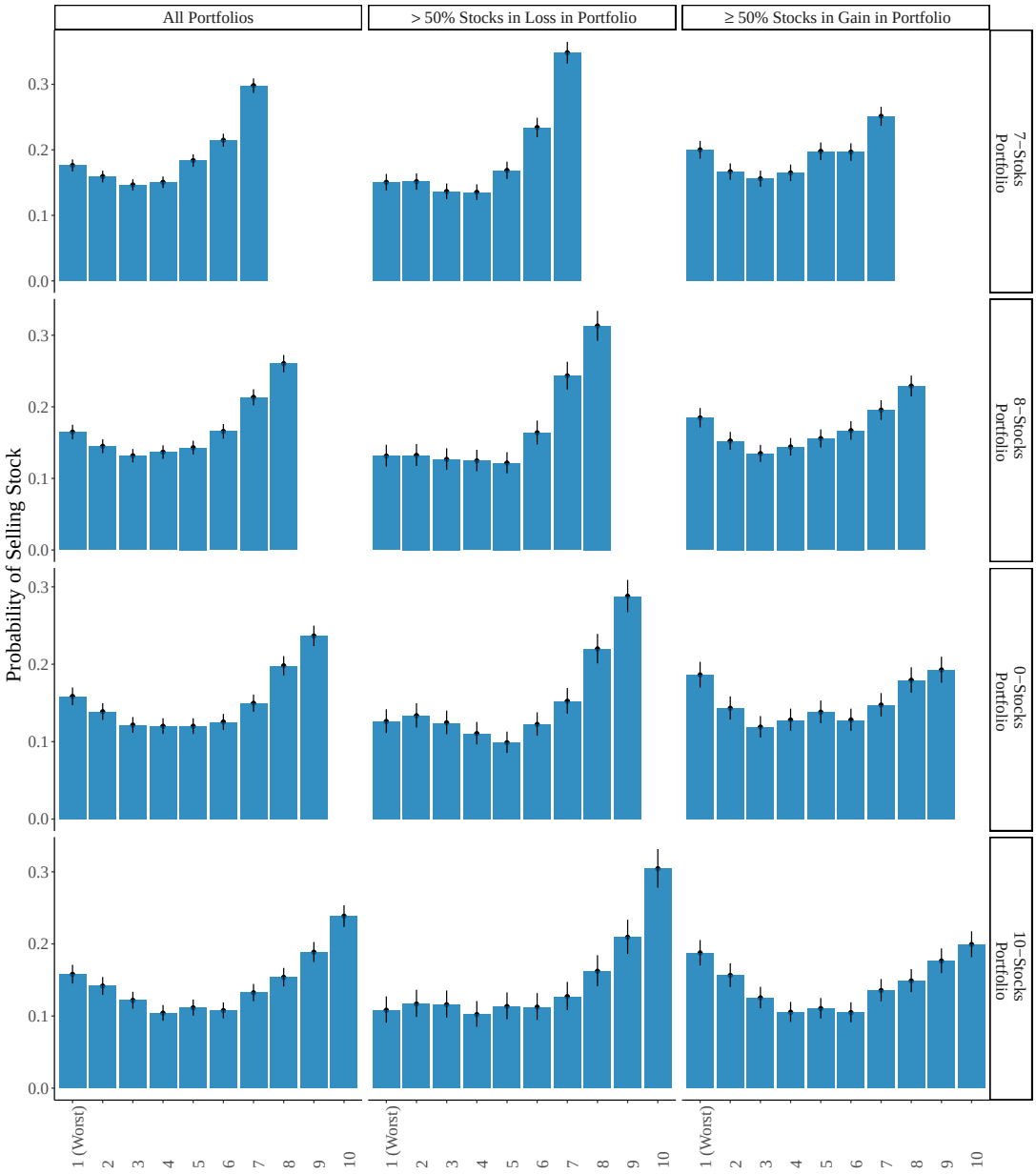
Note: The figure shows the frequency of sales by portfolio size. Panel A displays the average number of stocks sold on a trading day by portfolio size. The sample includes days in which the investor made at least one sale. Panel B shows the probability of a sale using observations at the account × stock × day level. For a better visualization, outliers at the 99th percentile of portfolio size were excluded. Vertical lines represent 95% confidence intervals.

Figure B4: Probability of Selling Stock for Small Portfolios, LDB Sell-Day Sample



Note: The figure shows selling probabilities for small-size portfolios. Portfolios of between three to six stocks are included separately across rows. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Each bar represents the probability of a sale in the indicated rank category. Column 1 aggregates all portfolios. Columns 2 and 3 split the data by portfolio composition. Column 2 includes portfolios composed mainly of loser stocks. Column 3 consists of the remaining portfolios. Vertical lines represent 95% confidence intervals.

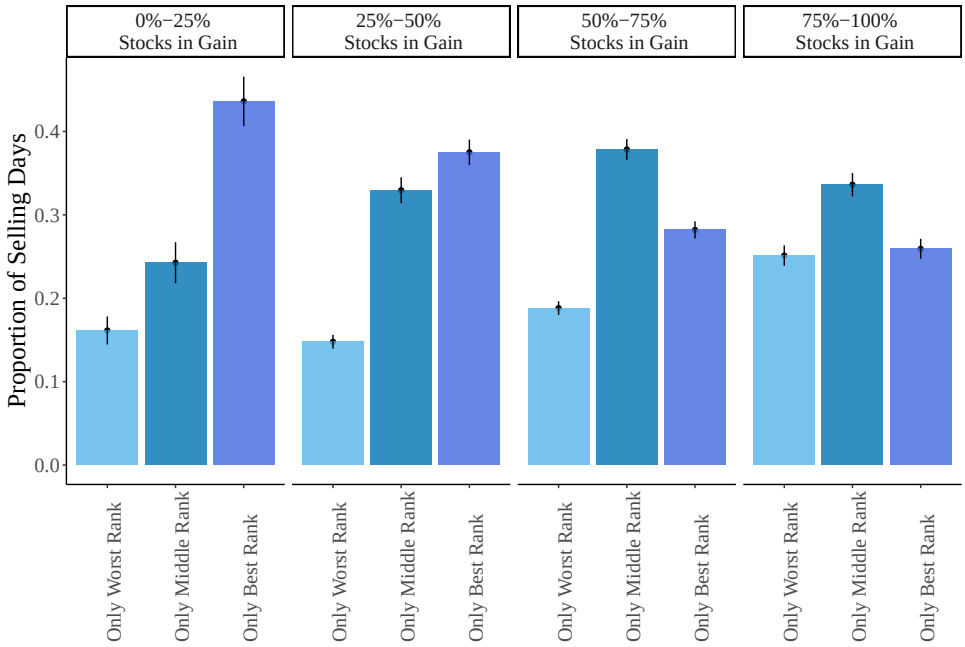
Figure B5: Probability of Selling Stock for Large Portfolios, LDB Sell-Day Sample



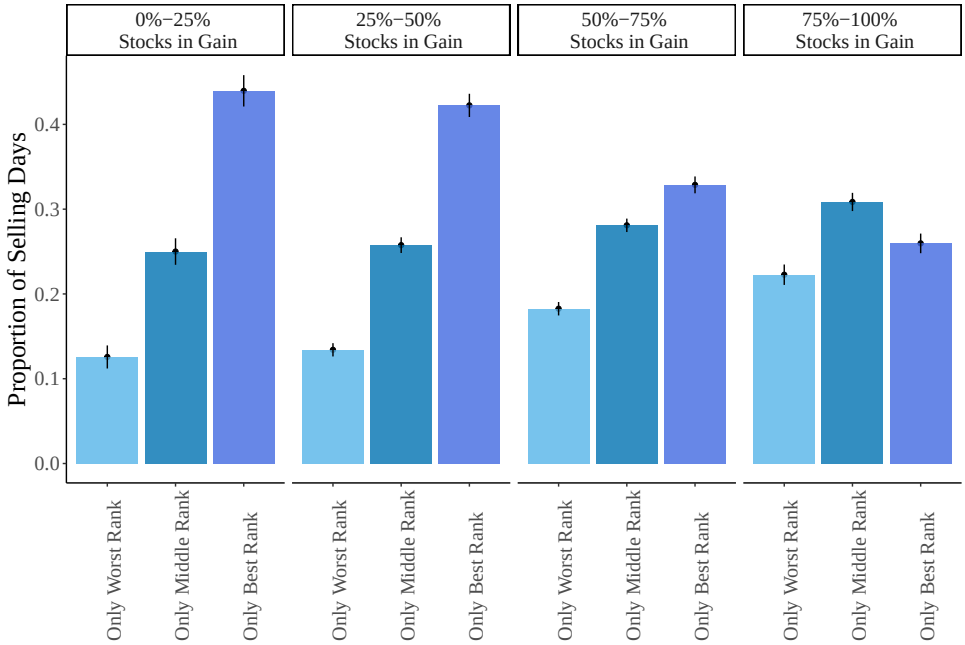
Note: The figure shows selling probabilities for large-size portfolios. Portfolios of between three to six stocks are included separately across rows. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Each bar represents the probability of a sale in the indicated rank category. Column 1 aggregates all portfolios. Columns 2 and 3 split the data by portfolio composition. Column 2 includes portfolios composed mainly of loser stocks. Column 3 consists of the remaining portfolios. Vertical lines represent 95% confidence intervals.

Figure B6: Proportion of Selling Days by Portfolio Composition, LDB Sample

(A) Best/Worst Ranks Defined as the Top/Bottom Two Positions

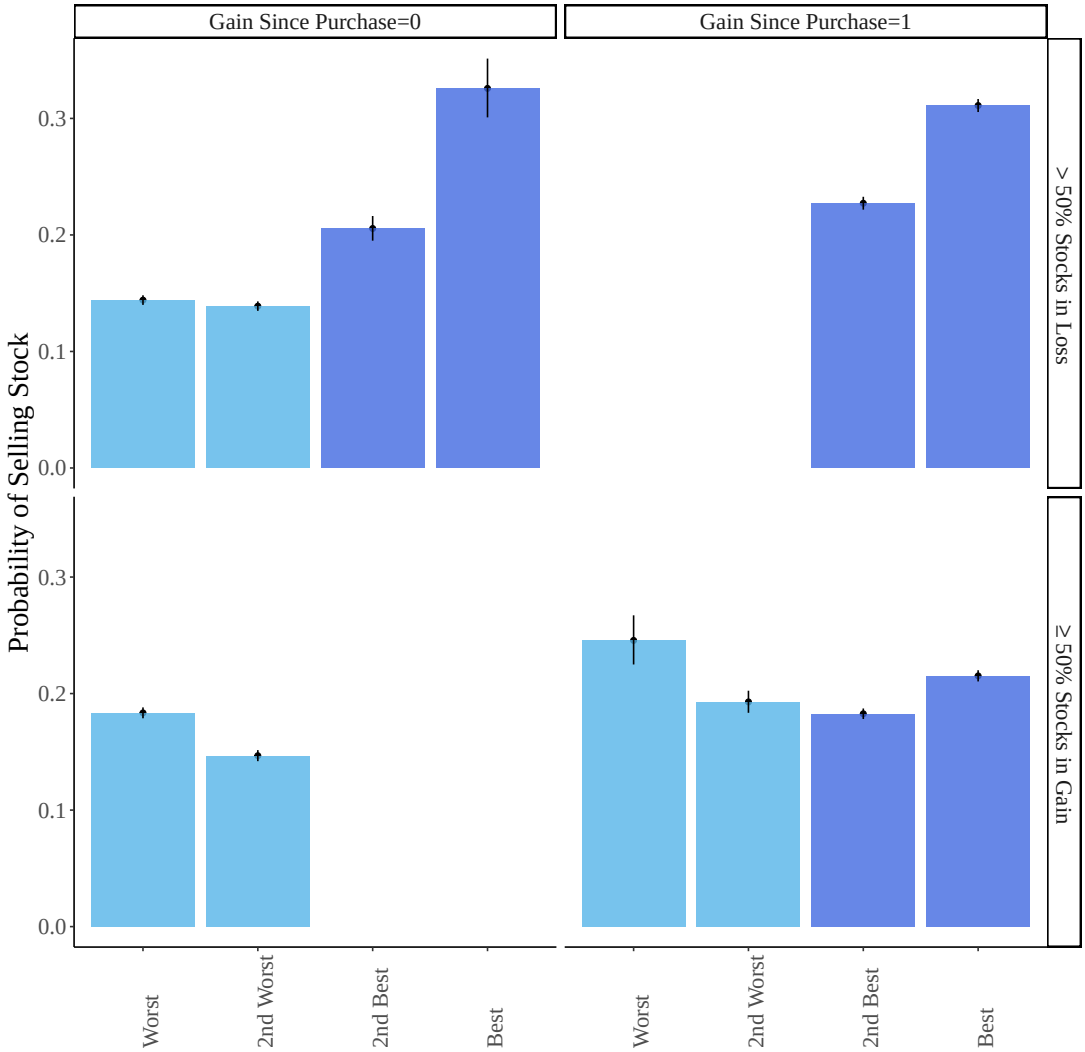


(B) Best/Worst Ranks Defined as the Top Tercile/Bottom Tercile Positions



Note: The figure shows rank preferences using data at the account × days level. The sample includes days in which the investor made at least one sale. Panel A shows the proportion of sell days in which the investor sold stocks exclusively from the top two positions (*Only Best Rank*), the bottom two positions (*Only Worst Rank*), or positions in between (*Only Middle Rank*). Subpanels split the sample by the proportion of stocks in gain in the portfolio. Column 1 includes days in which over 75% of stocks in the portfolio were in loss; likewise, Column 4, days in which over 75% of stocks were in gain. Panel B repeats the same exercise, but now rank categories are defined based on terciles of the rank distribution. Vertical lines represent 95% confidence intervals.

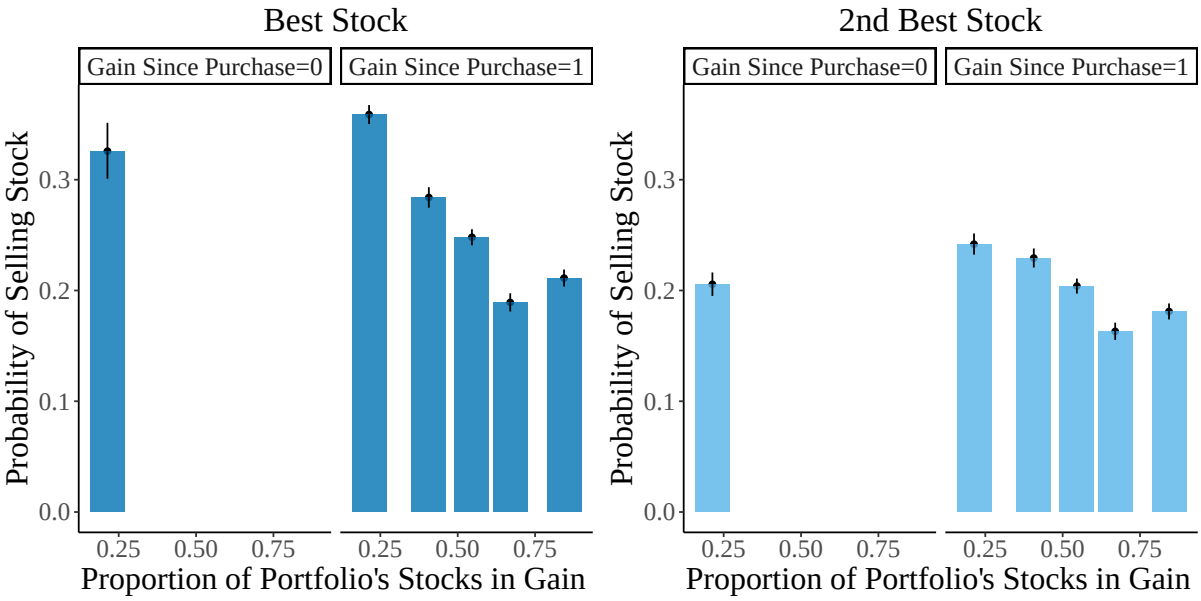
Figure B7: Probability of Selling by Portfolio Compositions and Gain Since Purchase, LDB Sell-Day Sample



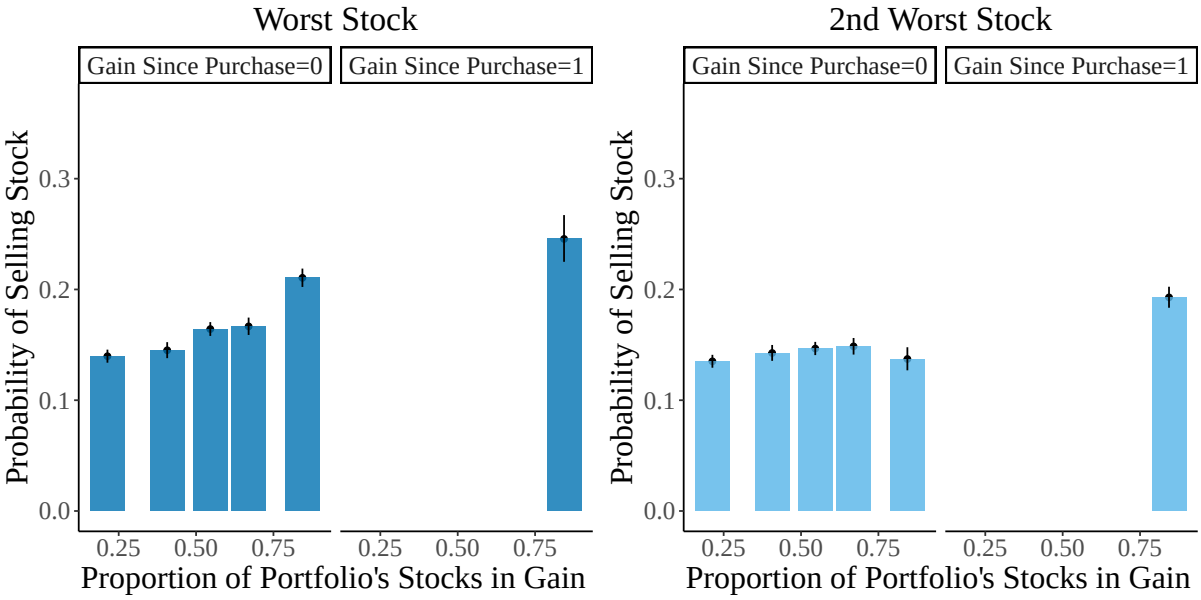
Note: The figure shows the probability of a sale by rank category, portfolio composition, and distinguishing winner from loser stocks. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Blue bars describe the top-two stocks' selling probabilities, while light blue bars, the bottom-two stocks' selling probabilities. Vertical lines represent 95% confidence intervals.

Figure B8: Rank Effects by Portfolio Composition, LDB Sell-Day Sample

(A) Best Two Positions



(B) Worst Two Positions



Note: The figure shows the probability of a sale by rank category, quintiles of portfolio performance, and distinguishing winner from loser stocks. The sample includes days in which the investor made at least one sale. Observations are at the account × stock × day level. Groups across the x-axis are defined based on quintiles on the proportion of stocks in gain in the portfolio. Panel A describes the top-two stocks' selling probabilities, while Panel B, the bottom-two stocks' selling probabilities. Vertical lines represent 95% confidence intervals.

Figure B9: Interaction Effect of the Portfolio Performance by Stock' Performance in the Past Week, Month, and Quarter, LDB Sell-Day Sample

Note: The figure shows the frequency of sales by portfolio size. Panel A displays the average number of stocks sold on a trading day by portfolio size. The sample includes days in which the investor made at least one sale. Panel B shows the probability of a sale using observations at the account × stock × day level. For a better visualization, outliers at the 99th percentile of portfolio size were excluded. Vertical lines represent 95% confidence intervals.

Table B1: Sample Selection in LDB Dataset

	Accounts	Sells
Starting Sample	126465	1329394
Drop due to:		
Retaining Common Stocks	22267	441755
Excluding Account × Stocks with Missing NCUSIP	562	15986
Excluding Account × Stocks with Potential Errors in Transactions (with trades displaying negative quantities but positive principal amounts, and vice versa)	9	773
Combining Multiple Intraday Trades (Excluding Trades with Zero Net Quantities Traded)	15	28870
Excluding Account × Stocks with Negative Commissions	522	19579
Excluding Account with Positions in January 1991	52173	534549
Excluding Account with Positions Before the First Recorded Transactions	7982	43588
Excluding Account × Stocks with Missing Adjusted Quantities or Prices	504	4469
Excluding Account × Stocks with Negative Holdings (Short Positions)	3555	58891
Excluding Account × Stocks × Days when a Position Stars	7541	0
Excluding Account × Stocks × Days whith Missing Prices on $t-1$	202	140
Excluding Accounts × Days with No Sells (i.e., Retaining Selling Days)	5757	0
Cleaned Sample	25376	180794
Drop due to:		
Retaining Account × Stocks × Days with Five Stocks	18293	101646
Baseline sample	7083	79148

Note: The table detail the steps in sample selection. The starting sample includes all accounts with trading records in the LDB dataset. Sells in Column 2 include all the stocks' liquidations or partial sells in the data. The largest drops, in steps 6 and 7, restrict the data to new accounts for which we know the purchase price of all stocks in the portfolio. This is accomplished by i) excluding accounts present in the first month of the position files (the LDB raw data comprise a set of files with monthly position information and an additional file with daily trading activity); and ii) excluding accounts for which the position files reveal that the account has held stocks before the first transaction registered in the file of trading activity. The final drop restricts the data to portfolios containing at least five stocks.

Table B2: Accounts Summary Statistics, LDB Sample

	Mean	Min	p25	p50	p75	Max
Account Characteristics						
Account Tenure (years)	1.324	0.000	0.000	0.748	2.285	5.770
Portfolio Value (£10000)	5.665	0.000	1.446	2.764	5.905	282.736
Conditional Number of Stocks	7.557	5.000	5.000	6.000	8.000	87.000
Sell days (% all market open days)	29.068	0.152	1.333	3.281	100.000	100.000
N Accounts	7083					

Note: The table presents summary statistics for new accounts. Account tenure is measured on the final day of the data period. Portfolio value is the value of all securities within the portfolio at market prices. Portfolio value and number of stocks are measured as within-account averages of values at the first day of each calendar month in the data period. Number of stocks is computed including only the set of days in which the account had at least 5 stocks in their portfolio. Sell days is the percentage of market open days the account is open in the data period and the account holder made at least one sale.

Table B3: Proportion of Stocks Sold by Rank Category, LDB Sample

	Sell-Day-Sample
Rank Group	
All Ranks	0.1349
Best	0.2632
2nd Best	0.2026
Middle	0.0976
2nd Worst	0.1483
Worst	0.1657
Rank Effect	
Best-Middle	0.1656***
	(0.0041)
Worst-Middle	0.0681***
	(0.0040)
Observations	586588

Note: The table presents the ratios of stocks that are sold in the indicated rank category divided by all stocks in that category. For example, the Best row reports #Best Sold/(#Best Sold+#Best Not Sold). Ratios are computed using observations are at the account × stock × day level. Column 1 includes days in which the investor made at least one sale; while Column 2, days in which the investor made at least one login to their account. The last rows present the difference between the indicated groups with standard errors clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table B4: Proportion of Stocks Sold by Rank, 5-Stocks-Portfolios, LDB Sample

	Sell-Day-Sample
Rank Group	
All Ranks	0.2524
Best	0.3732
2nd Best	0.2693
Middle	0.2127
2nd Worst	0.1923
Worst	0.2145
Rank Effect	
Best-Middle	0.1606***
	(0.0079)
Worst-Middle	0.0018
	(0.0065)
Observations	55675

Note: The table presents the ratios of stocks that are sold in the indicated rank category divided by all stocks in that category. The table is restricted to portfolios composed by five stocks. For example, the Best row reports #Best Sold/(#Best Sold+#Best Not Sold). Ratios are computed using observations are at the account × stock × day level. Column 1 includes days in which the investor made at least one sale; while Column 2, days in which the investor made at least one login to their account. The last rows present the difference between the indicated groups with standard errors clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table B5: Copy of Table 5 in Hartzmark (2015), Estimates of the Rank Effect

Table 5
Rank effect for individual investors with controls for past performance when all positions in a portfolio are at a gain or loss

	All gain	All loss
Best	0.117	0.045
	(8.31)	(2.09)
Worst	0.062	0.058
	(5.29)	(3.10)
2nd best	0.073	0.007
	(7.19)	(0.41)
2nd worst	0.040	0.025
	(3.88)	(1.64)
Return	0.001	0.119
	(0.04)	(1.35)
Additional controls	x	x
Observations	23,679	8,898
R^2	0.013	0.012

Note: The table presents a copy of Table 5 Hartzmark (2015). The table displays marginal effects from logit regressions of a dummy variable equal to one if a stock is sold on characteristics of the stock being held. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Additional controls include $Return$, $Return * \sqrt[2]{HoldingDays}$, $Variance$, and $\sqrt[2]{HoldingDays}$. The top number is the coefficient, and the lower number in parentheses is the t-statistic. Standard errors are clustered by account and day.

Table B6: Estimates of the Rank Effect, LDB Sell-Day Sample

	$Sale_{ijt}$		
	All-Gain	Mix	All-Loss
Rank Effects (Ref: Middle)			
Best	0.1098***	0.1746***	0.1235***
	(0.0155)	(0.0045)	(0.0242)
2nd Best	0.0757***	0.1066***	0.0589***
	(0.0134)	(0.0029)	(0.0191)
2nd Worst	0.0396***	0.0519***	0.0454**
	(0.0128)	(0.0030)	(0.0189)
Worst	0.0751***	0.0747***	0.0648***
	(0.0153)	(0.0037)	(0.0233)
Return Since Purchase (%)	0.0007**	0.0007***	0.0011
	(0.0004)	(0.0001)	(0.0008)
Constant	0.1663***	0.1320***	0.2315***
	(0.0134)	(0.0035)	(0.0380)
Additional Controls	YES	YES	YES
Observations	10,526	563,881	8,975
R2	0.0132	0.0326	0.0180

Note: The table presents ordinary least squares regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Additional controls include $Return$, $Return * \sqrt[2]{HoldingDays}$, $Variance$, and $\sqrt[2]{HoldingDays}$. Returns are winsorized at the 1% and 99% levels to remove the effect of outliers. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B7: Proportion of Stocks Sold by Rank Categories and Investors' Portfolio Composition, LDB Sell-Day Sample

Panel (A): Portfolios with All Stocks in Gain

		Subsamples of Portfolios			
	All Portfolios	5 Stocks	7 Stocks	9 Stocks	11 Stocks
Rank Group					
All Ranks	0.2102	0.2647	0.2066	0.1435	0.1491
Best	0.2578	0.3069	0.2535	0.1944	0.0800
2nd Best	0.2347	0.2597	0.2347	0.2222	0.1200
Middle	0.1659	0.2306	0.1815	0.1194	0.1429
2nd Worst	0.2103	0.2556	0.1925	0.0694	0.2000
Worst	0.2456	0.2708	0.2207	0.2083	0.2400
Rank Effect					
Best-Middle	0.0918***	0.0764***	0.0720**	0.0750	-0.0629
	(0.0136)	(0.0250)	(0.0306)	(0.0572)	(0.0699)
Worst-Middle	0.0797***	0.0403	0.0391	0.0889	0.0971
	(0.0153)	(0.0264)	(0.0399)	(0.0544)	(0.0884)
Observations	10576	3600	1491	648	275

Panel (B): Portfolios with All Stocks in Loss

	All Portfolios	5 Stocks	7 Stocks	9 Stocks	11 Stocks
Rank Group					
All Ranks	0.2251	0.2695	0.2130	0.1725	0.1773
Best	0.3258	0.3247	0.2994	0.2090	0.5000
2nd Best	0.2561	0.2795	0.2216	0.2090	0.2500
Middle	0.1865	0.2601	0.1896	0.1612	0.1357
2nd Worst	0.2098	0.2310	0.2036	0.2090	0.1000
Worst	0.2106	0.2520	0.1976	0.1194	0.1500
Rank Effect					
Best-Middle	0.1392***	0.0646**	0.1098**	0.0478	0.3643***
	(0.0231)	(0.0304)	(0.0428)	(0.0604)	(0.1004)
Worst-Middle	0.0241	-0.0081	0.0080	-0.0418	0.0143
	(0.0154)	(0.0261)	(0.0337)	(0.0443)	(0.0660)
Observations	9039	3095	1169	603	220

Panel (C): Portfolios with a Mix of Stocks in Gain and in Loss

	All Portfolios	5 Stocks	7 Stocks	9 Stocks	11 Stocks
Rank Group					
All Ranks	0.1321	0.2504	0.1885	0.1517	0.1291
Best	0.2618	0.3812	0.2993	0.2377	0.2210
2nd Best	0.2002	0.2694	0.2136	0.1973	0.1669
Middle	0.0959	0.2084	0.1586	0.1267	0.1074
2nd Worst	0.1448	0.1852	0.1568	0.1387	0.1312
Worst	0.1621	0.2079	0.1739	0.1581	0.1486
Rank Effect					
Best-Middle	0.1659***	0.1728***	0.1407***	0.1110***	0.1136***
	(0.0042)	(0.0084)	(0.0087)	(0.0097)	(0.0113)
Worst-Middle	0.0662***	-0.0004	0.0153**	0.0314***	0.0412***
	(0.0039)	(0.0069)	(0.0069)	(0.0073)	(0.0095)
Observations	566973	48980	43876	35172	27676

Note: The table presents the ratios of stocks that are sold in the indicated rank category by the investor's portfolio composition. Column 1 includes all portfolios. Columns 2-5 split the data by the proportion of stocks in gain in the portfolios. Ratios are computed using observations at the account × stock × day level. The sample includes days in which the investor made at least one sale. Only the best/worst two stocks are included in the sample. The last rows present the difference between the indicated groups with standard errors clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table B8: Proportion of Selling Days by Rank Categories, LDB Sample

Panel (A): Non Mutually Exclusive Rank Categories

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
Any Best Rank	0.4274	0.5557	0.4767	0.3802	0.3615
Any Middle Rank	0.4693	0.3773	0.4570	0.5110	0.4661
Any Worst Rank	0.2804	0.2589	0.2367	0.2830	0.3555
Rank Effect					
Any Best-Any Middle	-0.0419***	0.1784***	0.0196	-0.1308***	-0.1046***
	(0.0102)	(0.0266)	(0.0152)	(0.0111)	(0.0123)
Any Worst-Any Middle	-0.1889***	-0.1184***	-0.2203***	-0.2280***	-0.1106***
	(0.0097)	(0.0321)	(0.0127)	(0.0097)	(0.0118)
Observations	56280	7448	16093	21997	10742

Panel (B): Mutually Exclusive Rank Categories

		Portfolio Type (% of Portfolio's Stocks in Gain)			
	All Portfolios	0%-25%	25%-50%	50%-75%	75%-100%
Rank Group					
Only Best Rank	0.3246	0.4361	0.3750	0.2819	0.2593
Only Middle Rank	0.3384	0.2426	0.3295	0.3785	0.3362
Only Worst Rank	0.1851	0.1614	0.1479	0.1882	0.2512
Rank Effect					
Only Best-Only Middle	-0.0138	0.1935***	0.0455***	-0.0965***	-0.0769***
	(0.0097)	(0.0266)	(0.0146)	(0.0104)	(0.0114)
Only Worst-Only Middle	-0.1533***	-0.0812***	-0.1816***	-0.1903***	-0.0850***
	(0.0078)	(0.0197)	(0.0106)	(0.0092)	(0.0113)
Observations	56280	7448	16093	21997	10742

Note: The table shows rank preferences using data at the account × day level. The sample includes days in which the investor made at least one sale. Panel A shows the proportion of sell days in which the investor sold any stock from the top two positions (*Any Best Rank*), the bottom two positions (*Any Worst Rank*), or positions in between (*Any Middle Rank*). Proportions are not mutually exclusive, i.e., observations from an investor selling a position from the top rank and another from the middle rank will contribute to the computation of proportions for these two rank categories. Column 1 displays proportions for the whole sample. Columns 2 to 5 split the sample by the proportion of stocks in gain in the portfolio. Column 2 includes days in which over 75% of stocks in the portfolio were in loss; likewise, Column 4, days in which over 75% of stocks were in gain. Panel B repeats the same exercise, but proportions are computed including days when the investor sells stocks in only one rank category (i.e., proportions are mutually exclusive). Standard errors in parentheses are clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table B9: Estimates of the Rank Effect, LDB Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	-0.0243***	-0.0282***	0.0116*
	(0.0026)	(0.0027)	(0.0059)
2nd Best	0.0341***	-0.0035	0.0835***
	(0.0046)	(0.0062)	(0.0102)
Best	0.1018***	0.0609***	0.2183***
	(0.0053)	(0.0065)	(0.0108)
2nd Worst × Proportion of Stocks in Gain			-0.0744***
			(0.0112)
2nd Best × Proportion of Stocks in Gain			-0.1565***
			(0.0160)
Best × Proportion of Stocks in Gain			-0.2917***
			(0.0167)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)		-0.0341***	0.0984***
		(0.0059)	(0.0107)
Number of Stocks (10 stocks)	-0.0494***	-0.0488***	-0.0493***
	(0.0042)	(0.0040)	(0.0041)
Days Since Purchase (100 days)	-0.0109***	-0.0108***	-0.0100***
	(0.0004)	(0.0004)	(0.0004)
Gain Since Purchase=1		0.0432***	0.0372***
		(0.0054)	(0.0054)
Constant	0.2561***	0.2716***	0.2006***
	(0.0048)	(0.0050)	(0.0068)
Observations	225,120	225,120	225,120
R^2	0.0343	0.0349	0.0388

Note: The table presents ordinary least squares regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B10: Estimates of the Rank Effect, Fixed Effects, LDB Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0104*	0.0271*	0.0291**
	(0.0059)	(0.0145)	(0.0148)
2nd Best	0.0800***	0.1162***	0.1328***
	(0.0098)	(0.0186)	(0.0199)
Best	0.2157***	0.2324***	0.2554***
	(0.0108)	(0.0206)	(0.0223)
2nd Worst × Proportion of Stocks in Gain	-0.0740***	-0.0861***	-0.0896***
	(0.0112)	(0.0259)	(0.0266)
2nd Best × Proportion of Stocks in Gain	-0.1505***	-0.2027***	-0.2151***
	(0.0159)	(0.0290)	(0.0311)
Best × Proportion of Stocks in Gain	-0.2855***	-0.3330***	-0.3616***
	(0.0166)	(0.0280)	(0.0304)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0734***	0.1225***	0.1298***
	(0.0101)	(0.0191)	(0.0224)
Number of Stocks (10 stocks)	-0.0432***	-0.0439***	-0.0524***
	(0.0053)	(0.0032)	(0.0067)
Days Since Purchase (100 days)	-0.0115***	-0.0066***	-0.0070***
	(0.0004)	(0.0008)	(0.0011)
Gain Since Purchase=1	0.0372***	0.0290**	0.0218*
	(0.0055)	(0.0120)	(0.0127)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	225,120	225,120	225,120
R^2	0.0808	0.8770	0.9047

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B11: Estimates of the Rank Effect
Including Continuous Returns Since Purchase, LDB Sell-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Rank Effects (Ref: Worst)				
2nd Worst	0.0132**	0.0206***	0.0275*	0.0380***
	(0.0061)	(0.0062)	(0.0145)	(0.0147)
2nd Best	0.0866***	0.1075***	0.1137***	0.1553***
	(0.0103)	(0.0100)	(0.0196)	(0.0207)
Best	0.2236***	0.2441***	0.2369***	0.2844***
	(0.0117)	(0.0116)	(0.0217)	(0.0231)
2nd Worst × Proportion of Stocks in Gain	-0.0750***	-0.0777***	-0.0851***	-0.0908***
	(0.0113)	(0.0113)	(0.0259)	(0.0266)
2nd Best × Proportion of Stocks in Gain	-0.1511***	-0.1693***	-0.1742***	-0.2067***
	(0.0161)	(0.0158)	(0.0296)	(0.0313)
Best × Proportion of Stocks in Gain	-0.2831***	-0.3018***	-0.2974***	-0.3452***
	(0.0173)	(0.0169)	(0.0285)	(0.0309)
Portfolio/Stock Controls				
Proportion of Stocks in Gain (0-1)	0.1014***	0.0928***	0.1203***	0.1359***
	(0.0111)	(0.0103)	(0.0194)	(0.0227)
Number of Stocks (10 stocks)	-0.0484***	-0.0448***	-0.0405***	-0.0513***
	(0.0043)	(0.0057)	(0.0032)	(0.0067)
Days Since Purchase (100 days)	-0.0097***	-0.0117***	-0.0038***	-0.0052***
	(0.0004)	(0.0004)	(0.0009)	(0.0011)
Gain Since Purchase=1	0.0395***	0.0440***	0.0352***	0.0355***
	(0.0056)	(0.0058)	(0.0123)	(0.0131)
Return Since Purchase > 0 (%)	-0.0002***	-0.0001	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Return Since Purchase < 0 (%)	-0.0001	-0.0006***	0.0000	-0.0008***
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
	(0.0173)	(0.0169)	(0.0285)	(0.0309)
Constant	0.1941***			
	(0.0080)			
Account FE	NO	YES	NO	YES
Day × Stock FE	NO	NO	YES	YES
Observations	225,120	225,120	225,120	225,120
R^2	0.0389	0.0812	0.8772	0.9048

Note: The table presents fixed effects regression estimates of the main specification with the addition of continuous control variables for the return since purchase. Two separate variables are added to allow for different slopes for positive and negative returns. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B12: Estimates of the Rank Effect and the Disposition Effect, LDB Sell-Day Sample

	$Sale_{ijt}$							
	Controlling for the Interaction of the Disposition Effect with the Portfolio Composition			Specification (3) Omitting Rank Effects	Controlling for the Interaction of the Disposition Effect with a Portfolio Gain Dummy (An et al.' original measure)			Specification (7) Omitting Rank Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank Effects (Ref: Worst)								
2nd Worst	0.0013	0.0246*	0.0216		0.0080	0.0264*	0.0270*	
	(0.0060)	(0.0147)	(0.0151)		(0.0059)	(0.0145)	(0.0148)	
2nd Best	0.0394***	0.1032***	0.0960***		0.0663***	0.1104***	0.1208***	
	(0.0108)	(0.0211)	(0.0225)		(0.0099)	(0.0190)	(0.0203)	
Best	0.1561***	0.2135***	0.2018***		0.1967***	0.2241***	0.2376***	
	(0.0116)	(0.0247)	(0.0263)		(0.0107)	(0.0215)	(0.0229)	
2nd Worst × Proportion of Stocks in Gain	-0.0481***	-0.0790***	-0.0686**		-0.0667***	-0.0833***	-0.0824***	
	(0.0114)	(0.0265)	(0.0274)		(0.0113)	(0.0260)	(0.0268)	
2nd Best × Proportion of Stocks in Gain	-0.0659***	-0.1764***	-0.1389***		-0.1223***	-0.1914***	-0.1896***	
	(0.0172)	(0.0345)	(0.0372)		(0.0159)	(0.0301)	(0.0323)	
Best × Proportion of Stocks in Gain	-0.1726***	-0.2981***	-0.2616***		-0.2496***	-0.3182***	-0.3288***	
	(0.0181)	(0.0369)	(0.0394)		(0.0164)	(0.0302)	(0.0323)	
Portfolio/Stock Controls								
Proportion of Stocks in Gain (0-1)	0.0911***	0.1284***	0.1464***	0.0795***	0.0572***	0.1093***	0.1168***	
	(0.0103)	(0.0189)	(0.0225)	(0.0183)	(0.0103)	(0.0210)	(0.0244)	
Gain Since Purchase=1	0.1164***	0.0537***	0.0931***	0.2127***	0.0539***	0.0368***	0.0385***	0.1011***
	(0.0091)	(0.0203)	(0.0219)	(0.0160)	(0.0062)	(0.0135)	(0.0139)	(0.0101)
Gain Since Purchase=1 × Proportion of Stocks in Gain	-0.1510***	-0.0462	-0.1355***	-0.2858***				
	(0.0130)	(0.0286)	(0.0321)	(0.0243)				
Portfolio Gain=1					0.0145***	0.0113	0.0125	0.0282***
					(0.0033)	(0.0069)	(0.0081)	(0.0073)
Gain Since Purchase=1 × Portfolio Gain=1					-0.0324***	-0.0139	-0.0332***	-0.0834***
					(0.0052)	(0.0098)	(0.0107)	(0.0102)
Number of Stocks (10 stocks)	-0.0460***	-0.0445***	-0.0548***	-0.0574***	-0.0439***	-0.0442***	-0.0533***	-0.0536***
	(0.0058)	(0.0032)	(0.0069)	(0.0071)	(0.0055)	(0.0032)	(0.0068)	(0.0069)
Days Since Purchase (100 days)	-0.0114***	-0.0066***	-0.0069***	-0.0064***	-0.0114***	-0.0066***	-0.0067***	-0.0066***
	(0.0004)	(0.0008)	(0.0011)	(0.0010)	(0.0004)	(0.0008)	(0.0011)	(0.0010)
Account FE	YES	NO	YES	YES	YES	NO	YES	YES
Day × Stock FE	NO	YES	YES	YES	NO	YES	YES	YES
Observations	225,120	225,120	225,120	225,120	225,120	225,120	225,120	225,120
R^2	0.0817	0.8770	0.9048	0.9044	0.0811	0.8770	0.9047	0.9040

Note: The table presents fixed effects regression estimates of the main specification controlling for the disposition effect and its interaction with the portfolio performance. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Columns 1 to 4 measure portfolio performance as the proportion of stocks in gain in the portfolio. Columns 5 to 8 use An el al.' original measure of portfolio performance, a portfolio gain dummy that takes the value of one if the investor has a net gain in their holdings. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B13: Estimates of the Rank Effect, Complete Liquidations, Fixed Effects, LDB Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0086*	0.0187	0.0176
	(0.0052)	(0.0129)	(0.0132)
2nd Best	0.0727***	0.0902***	0.1058***
	(0.0080)	(0.0171)	(0.0181)
Best	0.1942***	0.2068***	0.2288***
	(0.0097)	(0.0194)	(0.0210)
2nd Worst × Proportion of Stocks in Gain	-0.0682***	-0.0713***	-0.0719***
	(0.0101)	(0.0231)	(0.0236)
2nd Best × Proportion of Stocks in Gain	-0.1566***	-0.1844***	-0.1944***
	(0.0133)	(0.0258)	(0.0274)
Best × Proportion of Stocks in Gain	-0.2908***	-0.3201***	-0.3454***
	(0.0151)	(0.0267)	(0.0287)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0798***	0.1090***	0.1218***
	(0.0091)	(0.0175)	(0.0205)
Number of Stocks (10 stocks)	-0.0325***	-0.0375***	-0.0348***
	(0.0040)	(0.0031)	(0.0054)
Days Since Purchase (100 days)	-0.0111***	-0.0092***	-0.0090***
	(0.0003)	(0.0007)	(0.0010)
Gain Since Purchase=1	0.0357***	0.0483***	0.0394***
	(0.0051)	(0.0116)	(0.0120)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	225,120	225,120	225,120
R^2	0.0905	0.8791	0.9083

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock (liquidating the entire position) and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B14: Estimates of the Rank Effect, Tax-Motivated Selling, Fixed Effects, LDB Sell-Day Sample

	$Sale_{ijt}$		
	Excluding Tax Liable Accounts		
	(1)	(2)	(3)
Rank Effects (Ref: Worst)			
2nd Worst	0.0128	-0.0249	-0.0551
	(0.0154)	(0.0629)	(0.0788)
2nd Best	0.0583***	0.0939	0.0732
	(0.0183)	(0.0758)	(0.1025)
Best	0.1953***	0.1782**	0.2372**
	(0.0235)	(0.0860)	(0.1143)
2nd Worst × Proportion of Stocks in Gain	-0.0863***	0.0225	0.1235
	(0.0268)	(0.1125)	(0.1361)
2nd Best × Proportion of Stocks in Gain	-0.1104***	-0.2169*	-0.0299
	(0.0311)	(0.1186)	(0.1496)
Best × Proportion of Stocks in Gain	-0.2630***	-0.3175***	-0.3238**
	(0.0362)	(0.1206)	(0.1469)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	0.0754***	0.0877	-0.1122
	(0.0201)	(0.0742)	(0.1076)
Number of Stocks (10 stocks)	-0.0525***	-0.0384***	-0.0866**
	(0.0098)	(0.0111)	(0.0366)
Days Since Purchase (100 days)	-0.0128***	-0.0025	-0.0077
	(0.0009)	(0.0031)	(0.0051)
Gain Since Purchase=1	0.0281**	0.0111	-0.0127
	(0.0118)	(0.0540)	(0.0727)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	43,428	43,428	43,428
R^2	0.0765	0.9684	0.9849

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. The analysis is restricted to 1310 accounts tax-exempt accounts, IRA or Keogh accounts. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B15: Estimates of the Alphabetical Rank Effect, Fixed Effects, LDB Sell-Day Sample

	$Sale_{ijt}$		
	(1)	(2)	(3)
Rank Effects (Ref: Last Name)			
2nd Last Name	0.0043	-0.0046	0.0057
	(0.0064)	(0.0141)	(0.0148)
2nd Name	0.0140**	0.0246	0.0239
	(0.0071)	(0.0233)	(0.0271)
First Name	0.0147**	0.0114	0.0010
	(0.0065)	(0.0233)	(0.0276)
2nd Last Name × Proportion of Stocks in Gain	-0.0127	-0.0007	-0.0017
	(0.0115)	(0.0248)	(0.0257)
2nd Name × Proportion of Stocks in Gain	-0.0256**	-0.0537**	-0.0474*
	(0.0122)	(0.0266)	(0.0284)
First Name × Proportion of Stocks in Gain	-0.0219*	-0.0258	-0.0116
	(0.0114)	(0.0249)	(0.0269)
Portfolio/Stock Controls			
Proportion of Stocks in Gain (0-1)	-0.0591***	-0.0141	-0.0147
	(0.0100)	(0.0178)	(0.0208)
Number of Stocks (10 stocks)	-0.0533***	-0.0517***	-0.0559***
	(0.0078)	(0.0033)	(0.0064)
Days Since Purchase (100 days)	-0.0058***	-0.0016**	0.0010
	(0.0004)	(0.0007)	(0.0010)
Gain Since Purchase=1	0.0736***	0.0511***	0.0612***
	(0.0040)	(0.0057)	(0.0063)
Account FE	YES	NO	YES
Day × Stock FE	NO	YES	YES
Observations	225,120	225,120	225,120
R^2	0.0756	0.8707	0.8982

Note: The table presents fixed effects regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.

Table B16: Proportion of Stocks Sold by Alphabetical Rank Category, LDB Sell-Days Sample

		Subsamples of Portfolios			
	All Portfolios	5 Stocks	7 Stocks	9 Stocks	11 Stocks
Rank Group					
All Ranks	0.1349	0.2524	0.1897	0.1519	0.1296
First	0.1743	0.2548	0.1960	0.1643	0.1347
Second	0.1715	0.2538	0.1904	0.1532	0.1273
Middle	0.1128	0.2600	0.1906	0.1507	0.1275
Second-Last	0.1676	0.2459	0.1789	0.1495	0.1378
Last	0.1686	0.2475	0.1907	0.1468	0.1339
Rank Effect					
First-Middle	0.0616***	-0.0052	0.0054	0.0136*	0.0073
	(0.0028)	(0.0065)	(0.0063)	(0.0076)	(0.0083)
Last-Middle	0.0558***	-0.0125*	0.0002	-0.0039	0.0065
	(0.0029)	(0.0069)	(0.0060)	(0.0067)	(0.0079)
Observations	586588	55675	46536	36423	28171

Note: The table presents the ratios of stocks that are sold in the indicated rank category divided by all stocks in that category. For example, the 'First' row reports #First Name Sold/(#First Name Sold+#First Name Not Sold). Ratios are computed using observations are at the account × stock × day level. The sample includes days in which the investor made at least one sale. Column 1 includes all portfolios. Columns 2 to 5 subset the data to portfolios of 5, 7, 9 and 11 stocks respectively. The last rows present the difference between the indicated groups with standard errors clustered by account and date. *p<0.1; **p<0.05; ***p<0.01.

Table B17: Copy of Table 8 in Hartzmark (2015), Estimates of the Alphabetical Rank Effect

Table 8
Alphabetical ordering by company name

	Selling		
	First and second name only [1]	Last and second to last name only [2]	All names [3]
First name	0.026		0.061
	(3.80)		(10.69)
Last name		0.029	0.061
		(3.52)	(11.02)
Stock x date FE	x	x	x
Observations	185,253	185,145	1,016,954

Note: The table presents a copy of Table 8 Hartzmark (2015). The table presents regressions of a sell dummy equal to one if a stock is sold on dummy variables based on the alphabetical ordering by company name ordering and stock by day fixed effects. First (Last) name is a dummy equal to one if the stock name is the first (last) name by alphabetical order in the portfolio. The top number is the coefficient, and the lower number in parentheses is the t-statistic. Standard errors are clustered by account and day.

Table B18: Estimates of the Alphabetical Rank Effect, LDB Sell-Day Sample

	$Sale_{ijt}$								
	1st and 2nd Names Only	Last and 2nd Last Names Only	All Names	1st and 2nd Names Only	Last and 2ns Last Names Only	All Names	1st and 2nd Names Only	Last and 2nd Last Names Only	All Names
First Name	0.0207***		0.0648***	0.0026		0.0320***	0.1415		0.0084
	(0.0061)		(0.0047)	(0.0061)		(0.0046)	(0.0932)		(0.0052)
Last Name		0.0242***	0.0523***		0.0058	0.0204***		0.0766	0.0010
		(0.0058)	(0.0046)		(0.0057)	(0.0046)		(0.1051)	(0.0055)
Number of Stocks (10 stocks)				-0.0530***	-0.0515***	-0.0341***			
				(0.0045)	(0.0040)	(0.0029)			
Day × Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Account × Day FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
Observations	112,560	112,560	586,588	112,560	112,560	586,588	112,560	112,560	586,588
R2	0.8740	0.8728	0.7826	0.8757	0.8744	0.7860	0.9981	0.9979	0.8734

Note: The table presents ordinary least squares regression estimates of the main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes days in which the investor made at least one sale. Standard errors are clustered by account and day. *p<0.1; **p<0.05; ***p<0.01.