Upward Mobility Bias in the Selling Decisions of Retail Traders [*]

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Abstract

Using price convexity as a measure of investor expectations about future price movement, the paper examines how its influence on selling decisions varies across stocks depending on their return ranks within a portfolio. We find that the negative association between price convexity and the selling propensity is significantly stronger for the lower-ranked stocks, and it becomes weaker as the stock rank in the portfolio increases. The findings suggest that upon observing price paths with similar convexity, traders expect their lower-ranked stocks to improve in performance in the future but not their higher-ranked stocks, implying the presence of upward mobility bias.

Keywords: Price Path; Investor Behavior; Behavioral Finance; Disposition Bias; Upward Mobility Bias

JEL classifications: G11; G40; G41

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1. Introduction

Over-extrapolation of realized outcomes while forecasting the future is commonly observed among financial market participants (Barberis, 2018; Cassella & Gulen, 2018; Da, Huang, & Jin, 2021; Greenwood & Shleifer, 2014; Gulen & Woeppel, 2022). Specifically, traders assign higher weights to more recent events compared to distant events while predicting outcomes such as returns and prices. As a result, they extrapolate the observed price path to continue in the future (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018). Similarly, analysts are known to expect the current trend to continue while forecasting the earnings of a company (Bordalo, Gennaioli, Porta, & Shleifer, 2019). Studies on extrapolation have focused on how traders form extrapolative expectations while forecasting the future performance of a single asset and its implications on trading decisions. However, with multiple assets in the portfolio, the degree to which traders extrapolate may not be uniform across all assets, as experimental studies indicate that relative performance can significantly influence expectations of future outcomes (Davidai & Gilovich, 2015b, 2016; Pettit, Doyle, Kim, & Hurwitz, 2022).

Consider two traders who have bought a stock at a particular time and now are evaluating its future potential. While both traders observe the same price path of the stock, the relative performance-based rank of the stock within their respective portfolios could be significantly different if their portfolios are non-overlapping. In such a scenario, expectations about future performance may vary as evidence suggests that individuals expect relatively low-ranked entities to improve excessively in their performance compared to high-ranked entities (Davidai & Gilovich, 2015b, 2016; Pettit et al., 2022). This asymmetry in expectations where an improvement in status is predicted to be more likely than a decrease, is referred to as upward mobility bias. For example, Davidai and Gilovich (2015b) document that while predicting future rankings of student performance, business schools, sports league teams, and employee performance, respondents are more likely to predict a rise than a fall in the rankings.[1]

Ranks of stocks in a portfolio setting are known to significantly impact trading decisions. Emphasizing the significance of relative performance-based ranking of the stock within a portfolio, Hartzmark (2015) documents that traders are more likely to sell the best and worst-ranked stocks in their portfolio. The phenomenon is popularly referred to as the "rank effect".[2] Therefore, we consider it important to investigate how the influence of extrapolative expectations on trading decisions could vary based on the relative rank of a stock within a portfolio.

If upward mobility bias shapes the expectations about future performance of ranked entities, the trader with the portfolio where the stock is ranked relatively lower may think that the stock's rank within the portfolio may improve in the future. In contrast, the trader with the portfolio where the stock has a higher rank, may not expect such improvement for the stock, despite both the traders observing the same price path.

In this paper, we examine the likely variation in the impact of extrapolative expectations on selling propensity based on the performance-ranks of stocks within traders' portfolio. Admittedly, a key challenge that we face in this investigation is the absence of a direct measure of the extrapolative expectations of individual investors. We attempt to address the challenge by employing price

[1] Davidai and Gilovich (2016) document upward mobility bias among subjects while forecasting future rank based on height and climatic phenomena such as temperature, rainfall level, and natural disasters.

[2] Quispe-Torreblanca (2021) documents the heterogeneity of the rank effect and finds that traders are more likely to sell their best-ranked stock when the portfolio performs poorly, but as the portfolio performs well, they are more likely to sell the worst-ranked stock.

convexity, proposed by Gulen and Woeppel (2022), as a proxy for the extrapolative expectations of investors. They document that price convexity effectively captures the extrapolative component of investor expectations and predicts future returns ranging from a week to a month. The measure places greater weight on recent price changes, which makes the value of price convexity higher for a series of price changes in which positive changes occur in the recent past. Therefore, price paths with high convexity are ones which could be extrapolated by traders to move favorably in the future.

Specifically, we investigate how the influence of price convexity on selling decisions varies based on the relative ranks of the stocks within the portfolio. Prior research documents a negative association between price convexity and selling propensity (Bansal & Jacob, 2022). If traders expect a lower-ranked stock to rise in rank with a greater probability than a higher-ranked stock, then the negative association between price convexity and selling propensity is likely to be stronger for the lower-ranked stocks. In other words, the negative impact of price convexity on the selling decisions is expected to be greater for low-ranked stocks compared to high-ranked stocks, as traders might be more likely to extrapolate the price path of a low-ranked stock in the portfolio. They might also expect a recovery in their poorly performing stocks to be more likely than a fall in their well-performing stocks. We use trader-level data from a discount brokerage that was first used by Odean (1998) and later by several studies that examined trader behavior in financial markets. The key findings of our study and their implications are as follows.

First, we find that the negative impact of price convexity on the selling propensity varies monotonically with the return ranks. The impact is greatest for the lowest-ranked stocks, followed by the stock ranked second to last, and the impact is the least for the stock having the highest return-rank in the portfolio. For instance, for a trader with five stocks in the portfolio, a one standard deviation (SD) increase in price convexity lowers the selling propensity by 3.8% for the stock ranked third in the portfolio. However, for the stock having return-rank four, the impact increases to 7.5%, and for the fifth-ranked stock, the impact increases to 8.8%.[3]. In effect, the negative association between extrapolative expectations and trading decisions exists only for the lower-ranked stocks but not for the higher-ranked stocks. Given, that the unconditional probability of selling any stock on any trading day by traders in our sample is around 23%, a decrease in the selling propensity by 8.8% for the lowest-ranked stock is economically significant. The difference in the association between selling propensity and price convexity based on return ranks suggests that, on observing a convex price path, traders expect their lower-ranked stocks to improve in performance to a greater degree than their higher-ranked stocks. The findings imply that the influence of extrapolative expectations on selling decisions is strongly dependent on return ranks.

The observed phenomenon could be affected by the magnitude of the difference in return between the higher and lower-ranked stocks. Therefore, we also investigate whether the phenomenon involving price convexity and ranks exists in the subsamples formed on the basis of the difference in the return of the highest- and lowest-ranked stocks. For the analysis, we create two subsamples based on below- and above-average differences in the returns of stocks ranked in the extremes within a portfolio. The results are consistent with the baseline analysis in both subsamples, implying that ranks influence trading decisions even when the magnitude of difference between returns of the highest- and the lowest-ranked stocks may not be large.

[3]The coefficient of $Convexity$ in column (4) of Table 4 is -3.8. For the stock having the second last rank (rank four), the net effect of one SD increase in price convexity on the selling propensity is - 7.5% (- 3.8 - 3.7). Similarly, for the last-ranked stock (rank five), the net impact of one SD increase in $Convexity$ on the selling propensity is - 8.8% (- 3.8 - 5.0).

Furthermore, we find that as the stock rank increases within the portfolio over the previous trading day, the negative association between price convexity and the selling propensity becomes weaker. In other words, after a rank increase in the portfolio from the last trading session, the probability that the stock is sold increases. The results hold even in subsamples where rank changes are caused by trivial price changes. It is likely that after an increase in rank, traders might assume that the scope to rise further is limited for a given level of price convexity. For example, if a stock is ranked five, then there are four positions to which it can move up, but if it is ranked second, then there is only one position to move up to. Therefore, after the stock has risen from rank five to rank two compared to the previous trading day, the portfolio holder may think that the scope for upward mobility is restricted and may become more inclined to sell the stock.

The overall evidence clearly highlights that while traders become less likely to sell their lower-ranked stocks after observing a convex price path, they trade differently in their higher-ranked stocks despite observing a price path with similarly high convexity. The asymmetry in the influence of price convexity on the selling decision suggests the presence of upward mobility bias (Davidai & Gilovich, 2015a, 2015b, 2016) where people expect an improvement in the status of a lower-ranked entity to be more likely.

Second, we investigate whether there is a variation in the association of convexity and selling propensity if stocks are ranked on the basis of a time-invariant criterion, alphabetical order. Stocks that appear at the extreme ends of an alphabetical order are likely to be more prominent in the minds of traders (Hartzmark, 2015). Since alphabetical ranks are not related to the performance of stocks, there is no reason to expect that an alphabetically lower-ranked stock will outperform an alphabetically higher-ranked stock. We observe that while variation in the association of convexity and selling propensity exists when ranks are assigned based on returns, it does not exist when ranks are based on alphabetical order. Therefore, it is less likely that the salience of the extreme-ranked stocks is the mechanism driving the baseline results. The contrast in the results for return-based ranks and alphabetical ranks strengthens the role of biased expectations as the explanation for the pattern in the association between selling propensity and price convexity as argued in upward mobility bias.

Third, we find that the asymmetry in the role of price convexity on selling decisions also prevails when examining the portfolios of traders who either have all their stocks in gains or all stocks in losses. Compared to the baseline analysis, in a subsample where all stocks have the same return sign, the difference between returns of the highest- and lowest-return-ranked stocks is likely to be less prominent in the minds of traders. Despite all stocks having the same return sign, we find that the negative association between price convexity and selling decisions is stronger for lower-ranked stocks in the portfolio. Therefore, our results imply that the relative ranks of stocks continue to influence trading decisions despite all stocks trading either at a gain or a loss. The findings also imply that the phenomenon documented in the baseline analysis is independent of the disposition effect, as the preference of booking gains over losses is absent when all stocks in the portfolio have the same return sign.

Lastly, we also find the prevalence of upward mobility bias in various subsamples of the data. We analyze the subsamples in which the overall portfolio is trading at a gain or a loss. If the tendency to focus on relative ranks of stocks is contingent on the performance of the overall portfolio, then it is likely that the prevalence of upward mobility bias could vary when the overall portfolio is at a gain versus a loss. However, we find that regardless of the overall performance of the portfolio, the negative association between price convexity and the selling propensity is stronger for the lower-ranked stocks. Given that prior research indicates that the disposition effect only exists when the portfolio is in a loss (An, Engelberg, Henriksson, Wang, & Williams, 2024), our findings again imply that upward mobility bias influences the selling decisions even when the disposition effect is absent.

We also document the consistency of the phenomenon across subsamples sorted by the trade intensity, traders' experience, investment amount, and demographics. We also perform several robustness checks employing different estimation methodologies, such as Probit and Cox proportional hazard models, extended sample analysis, and using an alternative measure for the price path. All robustness tests support the result on the influence of upward mobility bias in shaping the selling decisions of traders.

An alternative mechanism that could explain our results on the role of ranks in the association between convexity and selling propensity is investor expectations of mean-reversion of stock performance. Investors could expect the low-return (likely lower-ranked) stocks to recover and the high return (likely high ranked) stocks to fall from their current level, leading to a relatively higher selling of the higher-ranked stocks. However, several of our results suggest that the underlying phenomenon is upward mobility bias. First, we find that the asymmetric influence holds true even when there is no significant difference in the level of returns despite the variation in the ranks of stocks, which does not support a strong role for mean-reversion. Second, we document that the greater influence of convexity on the selling propensity for the low-ranked holds true even in portfolios even where all the constituent stocks are in gains or losses. Finally, we find that an increase (decrease) in the rank of a stock leads to a weakening (strengthening) of the impact of price convexity on the selling propensity. While the rank of a stock may undergo a change, it is not always accompanied by a significant change in the magnitude of return, which again casts doubts on the role the mean-reversion as the underlying mechanism.

Our paper makes contributions to several strands of literature. First, by documenting the varied influence of price convexity on selling decisions, conditional on portfolio context, we contribute to the literature on the role of extrapolative expectations on the decision-making process in the financial markets. Several experimental (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018) and empirical studies (Bansal & Jacob, 2022; Cassella & Gulen, 2018; Greenwood & Shleifer, 2014; Gulen & Woeppel, 2022) document that financial market participants extrapolate recent performance to the future and expect a continuation of the observed price trend. However, existing studies assume that extrapolative expectations uniformly impact trading decisions in all portfolio assets. Our study documents that the impact of extrapolative expectations on the trading decisions significantly varies based on the return rank of the stock within a portfolio. Second, by documenting that on observing a price path that could be extrapolated to continue rising in the future, traders refrain from selling their lower ranked stocks but not their higher ranked stocks, we document the presence of upward mobility bias (Davidai & Gilovich, 2015a, 2015b, 2016; Pettit et al., 2022). To our knowledge, no prior work has investigated the presence of upward mobility bias among traders in financial markets.

Third, our findings also extend the literature on how the relative ranking of stocks based on past performance, as documented by Hartzmark (2015), affects the selling decisions of retail traders. Unlike the rank effect Hartzmark (2015), where traders are more likely to sell stocks with the highest and lowest ranks, the negative influence of extrapolative expectations on selling decisions is strongest among stocks with the lowest rank and weakens with increasing return rank. Finally, we also contribute to the literature on investor behavior, in particular selling decisions and disposition effect (Barberis & Xiong, 2012; Ben-David & Hirshleifer, 2012; Odean, 1998), by demonstrating that upward mobility bias, involving distorted expectations about the future contributes to the reluctance of traders to sell their relatively poorly performing stocks.

The next section describes the data and the methodology adopted in the paper. Section 3 presents the key results of the paper, followed by a discussion in Section 4 and robustness checks in Section 5. Section 6 concludes our paper.

2. Data and Methodology

2.1. Data

In this study, we use trader-level data from a discount brokerage firm for the period 1991 to 1996. The same data set has been used in several studies such as Odean (1998), Ben-David and Hirshleifer (2012), Strahilevitz, Odean, and Barber (2011), Hartzmark (2015) and others. The data contain details of trades carried out by approximately 78,000 households and reports variables such as account number, stock identifier (CUSIP), date of transaction, trade price, and quantity of transaction. The data set contains transaction details for several product categories, ranging from common stocks, mutual funds, fixed income instruments, and others, but we restrict our analysis to common stocks, as this constitutes approximately 60% of the total investments made by all traders in the data set (Barber & Odean, 2000). Furthermore, we only consider those stock investments for which we could trace the CUSIP reported in the discount brokerage data to the CUSIP reported in the CRSP data base, as we require price information of the stocks.

We applied several criteria to select the baseline sample for analysis. We exclude investor-stock observations with negative trade commissions to avoid any transactions that may have been reversed by the broker later. The sample excludes stocks with a price per share less than $5, as a high-degree of speculative trading may take place in this category. Furthermore, we only include stocks that traded on all days in a year to ensure the liquidity of the sample stocks. From the selected trade data, we construct investor-stock level holding data to capture the open stock positions in the portfolio. For the baseline analysis, we only include the trader-date observations where the trader has carried out at least one transaction in any of their portfolio stocks. The opening buy transaction of any stock position is excluded from the analysis, as we do not observe intraday trade time stamps in the data. For the same reason, we also exclude any investor-stock position that has a holding period of less than one trading day. Lastly, we only include investor-stocks positions with a holding period of less than hundred days. The criteria that we adopt are similar to those employed by other studies that use the same data set as ours to examine the trading behavior of retail participants.

2.2. *Capturing extrapolative expectations from price convexity*

Outside survey-based elicitation of expectations of individuals about the future price movement, it is challenging to observe the expectations of traders about the future price movements of stocks. Therefore, we capture the extrapolative expectations of traders in our data using the framework proposed by Gulen and Woeppel (2022), based on the price path. Specifically, their measure captures the degree of convexity of a price series corresponding to the position of a trader in the stock market. The convexity is measured by computing how far the midpoint of the price series is from the average price. If the midpoint is significantly above the average of the price series, then it is a relatively convex price path. Higher convexity implies that the price changes towards the end of a price path have been in a positive direction. If traders were to extrapolate such a price path into the future, they may expect prices to continue to increase in the near term. The difference between the mid-point and the average is then standardized by dividing it by the average price to make it comparable across different stock positions. The convexity measure is as defined below:

$$Convexity = \frac{\frac{Price_{start} + Price_{last}}{2} - Price_{average}}{Price_{average}} \tag{1}$$

$Price_{start}$ is the first observation of the price series and $Price_{last}$ is the last observation since the initiation of the stock position. A simple average of $Price_{start}$ and $Price_{last}$ represents the midpoint of the price series. $Price_{average}$ is the average of all price points observed by a trader in the stock from the initiation of the position till the last price point.

Gulen and Woeppel (2022) argue that price convexity is a reliable measure of the extrapolative component of investor expectations. They show that when investor expectations are directly observed, convexity captures a substantial proportion of the variation in it. In addition, when the extrapolative component of the expectations is regressed on convexity, the proportion of variation explained by price convexity is more than 50%. The price convexity can be easily computed using the price data. Gulen and Woeppel (2022) argue that in cases where investor expectations are not directly available, price convexity is a reasonable proxy for capturing the extrapolative component of the expectation of the traders.

2.3. *Empirical Methodology*

Our empirical approach attempts to estimate the variation in the association between extrapolative expectations and the selling decisions of traders based on the relative ranks of the stocks within a trader's portfolio. We primarily employ a linear probability model (LPM), which has previously been used in studies such as Chang, Solomon, and Westerfield (2016) and Vasudevan (2023) to investigate variations in the trading behavior of retail participants in the stock market.[4] The exact specification of our baseline estimation model is as follows:

$$
\begin{aligned}
Sell_{ijt} = \quad & \beta_1\, Portfolio^{+}_{it} \; + \beta_2\, Stock^{+}{}_{ijt} \; + \beta_3\, Convexity_{ijt} + \\
& \beta_4 \sqrt{Days}_{ijt} \; + \beta_5\, Volatility_{jt} + \\
& \beta_6\, Convexity_{ijt} \times \textbf{\textit{Return Rank}}_{ijt} + \\
& \gamma_i + \theta_{return\ rank} + \delta_{j \times ym} + \kappa_t \; + \epsilon_{ijt}
\end{aligned}
\tag{2}
$$

$Sell_{ijt}$ takes a value of 1, if investor i sells the stock j on trading day t, else 0. $Portfolio^{+}_{it}$ captures whether the portfolio of investor i is trading at a gain or not as on day t. Similarly, $Stock^{+}{}_{ijt}$ captures whether stock j in trader $i's$ portfolio is in gains or not on day t. $Convexity_{ijt}$ is the convexity of the price path that trader i experiences in stock j from the start of the investment till trading day t. $Days_{ijt}$ measures the number of days the stock has been in trader $i's$ portfolio

[4] As a robustness check we also re-estimate our baseline results using alternative models such as Cox Proportional Hazard model and Probit, which are employed by studies such as An et al. (2024) and Seru, Shumway, and Stoffman (2010) to analyze the trade data of retail participants.

as on trading day t. $Volatility_{jt}$, is computed as the average absolute daily returns of stock j over the last 250 trading days from trading day t. Detailed descriptions of all key variables except *Return Rank*$_{ijt}$ are presented in Table 1.

Return Rank$_{ijt}$ is rank of the stock j in the portfolio of the trader i on trading day t based on their returns. It is a categorical variable with multiple levels that captures whether the stock occupies the first, second, second last, or last position in a portfolio based on its returns. The number of levels for which the effect is estimated and the corresponding reference level depend on the number of stocks in a trader's portfolio. For example, if there are five stocks in the portfolio, the reference level is taken as the third rank, and the estimated levels of ranks are the first, second, second last (fourth rank) and the last (fifth rank). Similarly, if there are three stocks in the portfolio, the reference level is taken as the second rank, and the estimated levels of ranks are the first and last (third rank). The reference and estimated levels of return-ranks that vary on the number of portfolio stocks are presented in Table 2.

All explanatory variables, except price convexity and return rank, have been employed in other studies such as Ben-David and Hirshleifer (2012) and An et al. (2024) and serve as standard control variables for analyzing this popular data set. The summary statistics for all variables are presented in Table 3.

The key parameter of interest is the coefficient of the interaction term between $Convexity$ and *Return Rank*. The sign of the interaction term estimates the effect of $Convexity$ on the selling propensity, which varies with the ranking of the stock in the portfolio, compared to the reference level. In all estimations, the reference-level impact of extrapolative expectations is the coefficient of $Convexity$.

Extending the case of a trader having five stocks in the portfolio, the reference level corresponds to the third ranked stock in the portfolio. Hence, the coefficient of $Convexity$ captures the influence of convexity on the selling propensity of the third-ranked stock in that case. The differential impact of convexity on other stocks that are ranked away from the reference level will be captured by the coefficient of the interaction term. If the sign of the interaction term ($Convexity$ $\times$ *Return Rank*) is negative for a particular rank, then it would imply that compared to the reference level, the association between $Convexity$ and the selling decision is more negative for the particular return rank. Building on the previous example, if the coefficient of interaction term $Convexity$ $\times$ *Rank: Last* is negative, then it would imply that one standard deviation (SD) increase in convexity leads to greater reduction in the selling propensity of the last-ranked stock (rank five) relative to the reference level (rank three). The net impact of convexity on the selling propensity of the last-ranked stock will be the sum of the coefficient of $Convexity$ and $Convexity$ $\times$ *Rank: Last*.

The estimation employs a saturated fixed effects model to account for the time-invariant and the time-variant unobserved heterogeneities that may influence the selling decisions of the traders. γ_i represents trader-level fixed effects that capture the influence of trader-specific characteristics that may not change over time but may influence trade decisions. For example, the level of diligence of the trader is likely to influence the trading decisions. $\theta_{return\ rank}$ absorb any impact that the ranking of a stock may have on the selling propensity. For example, Hartzmark (2015) document that traders are more likely to sell their best and worst ranked stock compared to other stocks in their portfolio. Such rank-specific effects will be taken into account by $\theta_{return\ rank}$, and as a result, the coefficients of the categorical variable *Return Rank*$_{ijt}$ will not be estimated. However, the coefficient of interaction terms $Convexity_{ijt}$ $\times$ *Return Rank*$_{ijt}$ will be estimated in all regressions.

$\delta_{j \times ym}$ will account for the impact of all characteristics of the stock level that vary at a year-month level, such as the earnings forecast, as well as those that may not vary over time, such as the tax code of the state where the company is headquartered. Lastly, κ_t accounts for the factors that can vary on a daily basis and can influence the trading behavior of market participants. For example, investor sentiment in the market on a particular trading day may affect trading at a market level. We compute multi-way robust standard errors clustered at investor, stock, and trading day levels.

3. Findings and Discussion

3.1. Baseline results: on the asymmetric influence of price convexity on selling decisions

We examine how the influence of price convexity on selling decisions varies based on the ranks of the stocks within a trader's portfolio by estimating Equation 2. The results, presented in Table 4, provide an estimate of the interaction between convexity and the return ranks of the stocks within the portfolio. The interaction effect captures the incremental impact of the price convexity on the selling propensity for a stock with a certain rank, relative to that of the reference rank. The definition of the reference rank for any portfolio depends on the number of stocks in the portfolio as described in Table 2.

The findings indicate that for the reference-level rank, the impact of price convexity (coefficient of $Convexity$) is negative and significant, suggesting that the selling propensity declines when traders observe a relatively convex price path. However, the influence of price convexity is not homogeneous across all stocks in the portfolio. For stocks ranked below the reference level, the negative association between price convexity and selling propensity is greater as compared to the reference level. Furthermore, the inverse association between convexity and the likelihood of selling becomes stronger, the lower the rank of the stock relative to the reference level. For example, in column (5) representing traders with five stocks in their portfolio, one standard deviation increase in the price convexity lowers the selling propensity by 3.8% for the reference level stock (third rank). However, for the second-last-ranked stock (rank four), the coefficient is 7.5% (-3.8 - 3.7), and for the stock ranked last (rank five), the probability further declines to 8.8% (-3.8 - 5.0). In contrast, as the return rank increases above the reference level, the negative impact of the price convexity becomes weaker. For example, in column (5), for the highest-ranked stock, the negative impact of price convexity is reversed. One standard deviation increase in price convexity increases the selling propensity by 2.6% (-3.8 + 6.4). The observed impact on selling propensity is economically significant as the unconditional probability of selling a stock by traders on any trading day in the sample is approximately 23%.

The results show that when traders expect the price of the lower-ranked stocks to rise in the future, as captured by price convexity, they show reluctance to sell the stock. However, on observing similar price convexity for their higher ranked stocks, their selling propensity increases. A likely explanation for the observed results is that traders believe that there is more room for improvement in the performance of their lower-ranked stocks relative to the high-ranked stocks. The results suggest that the association between price convexity and the selling propensity is significantly influenced by the return rank of a stock in a portfolio.

The estimated values of other explanatory variables are in line with previous studies that employ the same data set. Consistent with the findings of An et al. (2024), the sign of $Portfolio^{+}$ is negative and significant in all columns of Table 4, indicating that the probability of selling a stock is lower if the overall portfolio is in gain. The sign of $Stock^{+}$ is positive and significant in Table 4, highlighting the widespread prevalence of the disposition effect (Ben-David & Hirshleifer, 2012) among traders in our data. The sign and significance of $\sqrt{Days}_{ijt}$ indicates that the longer the stock is held in the portfolio, the more likely it is that the traders will sell it. Lastly, the selling propensity increases with the volatility of the stock, similar to the results in Nolte and Schneider (2018) and Ben-David and Hirshleifer (2012).

In the preceding analysis, as we employ return ranks, the estimated coefficient of the interaction term between price convexity and the return ranks could be impacted by the magnitude of return difference between the ranked stocks. To account for the possible impact of the return range, we investigate the prevalence of the phenomenon in situations where the return difference between the extreme-ranked stocks is relatively lower. In such portfolios, the ranked stocks will have very little difference in their return magnitude. As a result, the variation in the association of price convexity and selling decisions based on the ranks is less likely to be influenced by return differences. In contrast, when the return range between stocks is very high, the observed outcome could be influenced by the magnitude of the return difference between the extreme ranks and not the ranks themselves.

3.2. Estimation to account for return differences in high- and low-ranked stocks

To examine whether the differential association of price convexity with the selling decisions is reliably attributable to the ranks, we create sub-samples of portfolios with large and small differences in the returns of the extreme-ranked stocks. We split the baseline sample on the basis of the average value of the difference in the return of the top and the bottom ranked stocks in the portfolio. The results of the estimations are presented in Table 5. The two subsamples represent a significantly different distribution of range in returns for the extreme ranked stocks. For instance, the subsample that represents 'below average difference' with three stocks in the portfolio (column (3)) has a mean return difference of 3.8% (median 2.4%) between the highest- and lowest-ranked stocks. The corresponding figure for the 'above average difference' subsample (column (8)) is 27% (median 22.5%).

In both subsamples, we find a noticeable difference in the influence of price convexity on the selling decisions of the low-ranked versus the high-ranked stocks. Similar to the baseline estimation, an increase in $Convexity$ lowers the selling propensity at the reference level, and the magnitude of the impact is significantly greater for lower-ranked stocks. In contrast, the negative association between price convexity and selling propensity is completely reversed for the higher ranked stocks in the portfolio. For example, in column (3) of Table 5, for a trader holding three stocks (reference rank two), a one-standard deviation increase in convexity lowers the selling propensity for the third-ranked stock by 12% (-3.9% - 8.1%), but the effect reverses to an increase in the selling propensity by 2% (-3.9% + 5.9%) for the highest-ranked stock. The corresponding values for the subsample with the above-average difference in the return between the extremely ranked stocks, in column (8) of Table 5, are -11.9% (-3.7% - 8.2%) and 0.2% (-3.7% + 3.9%).

The results in Table 5 reinforce the phenomenon documented in the baseline analysis. It also suggests that even when the return difference between the highest- and lowest-ranked stocks is not very high, traders still pay attention to the relative rank of the stocks in the portfolio, which continues to influence their trading decisions. The findings suggest that the ranks independently influence the association between the selling propensity and price convexity, irrespective of the return difference between extreme ranked stocks. The pattern in the influence of extrapolative expectations, captured by convexity, on the selling propensity across the ranked stocks indicates that traders expect their lower-ranked stocks to improve in their performance but not the higher-ranked stocks.

As our results so far suggest that ranks significantly impact the association between extrapolative expectations and selling propensity, it is likely that an increase or decrease in the rank also exhibits a consistent pattern of influence. More specifically, an increase in the rank could create the impression that the scope for further improvement in the relative performance is lower, despite observing a convex price path. Hence, traders are more likely to sell a stock following an increase in its rank. In the following section, we examine the role of rank changes.

3.3. Price convexity and selling propensity: Impact of rank changes

Rank changes within a trader's portfolio could be accompanied by trivial price changes, leading to no material difference in the absolute performance of the stocks in terms of returns. In such cases, if price convexity continues to influence the selling decisions in an asymmetric manner based on the ranks of the stocks, then the underlying phenomenon is driven by relative performance and not the absolute performance. Given the focus of the investigation on rank variations associated with small changes in prices, we split the baseline data into two subsamples based on the average absolute daily returns. The subsamples where the return difference is below average represent cases where daily rank changes follow relatively trivial price changes over the previous day.

In Table 6, we present the results of the interaction between the price convexity and the change in return rank from the previous trading day. In the estimations representing rank changes linked to small price changes, columns (2) to (6), we find consistent results that an increase in the price convexity of a stock lowers the selling probability. In this subsample similar to earlier estimations, if the stock experiences an increase in the return-rank within the portfolio, the magnitude of the negative association between price convexity and the selling propensity declines. For example, in column (4) of Table 6, one standard deviation increase in $Convexity$ leads to a lowering of the selling propensity by 4.2%. However, when the rank of the stock within the portfolio increases by one unit compared to the previous trading day, the magnitude of negative association between price convexity and probability of selling declines to 2.7% (-4.2 + 1.5). In contrast, the interaction term between rank changes and convexity is not uniformly significant for the subsample where the magnitude of price change accompanying the rank change is higher (columns (7)-(11)).

In Table 7, we find a similar pattern by interacting $Convexity$ with a dummy variable that captures an increase or decrease in the rank of a stock within the portfolio from the previous trading day. The indicator variable has three levels, and the reference level captures the scenarios when the rank of the stock within the portfolio remains unchanged compared to the previous day. The other two levels capture rank increase or decrease of a stock in the portfolio. In most estimations, in Table 7, we find that the coefficient of interaction term $Convexity \times$ *I(2. Rank Decline from t-1 to t)* is negative and significant. The results imply that the negative association between the selling propensity and convexity intensifies when the rank of a stock within the portfolio declines compared to the previous trading day.

The results suggest that when the rank of a stock increases, traders may think that any scope for further improvement in its performance becomes limited. Therefore, after an increase in rank, they rely less on extrapolative expectations and are more likely to sell the stock. For example, when a stock that currently has a return rank of two in the portfolio rises to become the highest ranked stock, traders may think that any room for further improvement within the portfolio is exhausted. In such a scenario, despite observing a convex price path, traders may think there is no room for further improvement in the relative performance of the stock. As a result, traders may increasingly prefer to sell the stock after an increase in its rank.

3.4. Pattern in the association between convexity and selling propensity: Does it suggest upward mobility bias?

In the analyses so far, we observe that the influence of price convexity on selling propensity depends on stock ranks, with traders being less likely to sell their lower-ranked stocks given a certain price path. The pattern exists irrespective of the return difference between the extreme ranked stocks, highlighting the important role of the ranks. Corroborating the role of ranks, we find that rank changes also influence the association between price convexity and selling decisions. The trading pattern revealed in the findings implies that for stocks with similar price convexity and return levels, the extent to which traders are willing to extrapolate the observed price path into the future depends on the return-rank of the stock within their respective portfolios.

Traders become less likely to sell their lower-ranked stocks after observing a convex price path that could be extrapolated to move upward in the future. Such a trading pattern suggests that traders expect the convex price paths of lower-ranked stocks to increase further in the future. However, they do not exhibit the same trading pattern in their higher-ranked stocks despite observing a price path with similar level of convexity. The asymmetry in the influence of price convexity on the selling decision suggests the presence of upward mobility bias (Davidai & Gilovich, 2015a, 2015b, 2016), in which subjects believe that an improvement in the performance of a low-ranked entity is more probable. In subsequent sections, we document several additional analyses to further examine the presence of upward mobility bias in the context of trading in financial markets.

3.5. Alternative ranking scheme based on a time-invariant criterion: Does it suggest upward mobility bias?

The upward mobility bias originates from the biased belief that the performance of the lower-ranked entities is more likely to improve than the performance of higher-ranked entities. However, it can exist in situations such as stock trading only when traders believe that the rankings can evolve over time. If entities are ranked on the basis of a criterion that is time-invariant, then the observed pattern should be absent. Hence, to examine whether upward mobility bias is indeed the underlying phenomenon behind the observed outcomes, we assess whether it exists when the stocks are ranked based on a time-invariant criterion.

The static criterion we employ to rank stocks, instead of returns, is the alphabetical order of the stock names. While return-based ranks can change frequently, alphabetical ranks cannot, as companies rarely change their names. If the association between price convexity and the selling propensity varies based on the alphabetical ranks of the stock, similar to return-based ranks in the preceding analyses, then we cannot ascribe the observed results to upward mobility bias. However, if the impact of price convexity on the selling choices does not vary significantly when stocks are ranked alphabetically, then the underlying phenomenon is likely to be related to future expectations and upward mobility bias. We test the same in Table 8.

We find that the coefficients of $Convexity \times$*Alphabetical Rank: Last* and $Convexity \times$*Alphabetical Rank: First* are statistically not different from zero. The results imply that, compared to the influence of $Convexity$ on selling decisions for reference levels of rank (based on alphabetical order), the influence on the highest and lowest ranked stocks is not statistically different. In other words, when stocks are ranked alphabetically, the influence of extrapolative expectations does not vary between stocks that are ranked differently. Based on the results, we can infer that when stocks are ranked according to a criterion unrelated to time-varying future expectations, trading choices are not in line with upward mobility bias.

Since we do not observe any heterogeneity in the association of convexity on selling decisions for stocks ranked stock ranked alphabetically, we can infer that the heterogeneity for return-based ranks in the preceding sections is attributable to upward mobility bias of traders.

3.6. Does upward mobility bias exist independent of the salience of ranks and the disposition effect?

Hartzmark (2015) document that the stocks that occupy the extreme ranks are more likely to be sold due to the salience of the extreme ranks. If upward mobility bias was resulting from the salience of the extreme ranks, then the phenomenon should have been present in both return-based and alphabetical ranking schemes. In Table 8, we do not observe any difference in the influence of extrapolative expectations on the selling propensity of the highest and lowest alphabetically ranked stocks. Hence, based on the results in Table 8, we can argue that the upward mobility bias is not driven by the salience of the extreme ranks.

The baseline results could partly reflect the tendency of traders to sell their winning stocks and hold on to their losing stocks. This may happen if the lower-ranked stocks are more likely to be those trading at a loss, and the higher-ranked stocks are those trading at a gain. However, the trading decisions are unlikely to be influenced by disposition bias, when all the stocks in the portfolio are either in gains or in losses. If the differential influence of price convexity across various return ranks continues to hold in such situations, then it could be argued that upward mobility bias exists independently of disposition effect. For this purpose, we create two sub-samples: a sub-sample of trader-day observations where all the stocks in the portfolio are at a gain and the other in which all the stocks in the portfolio are trading at a loss. We present the results in Table 9.

Columns (2)-(6) present the results for the subsamples where all the stocks in the portfolio are in gains, and columns (7)-(11) present the results where all stocks are in losses. In line with the baseline analysis, in most cases, we find that the coefficient of $Convexity$ is negative and significant, indicating that an increase in the convexity of the price path lowers the selling propensity even in the cases where all stocks in the portfolio have the same return sign. Furthermore, the coefficient of the interaction term $Convexity \times$ *Rank: First* is also positive and significant in most columns. Hence, the negative association of price convexity with the selling propensity is weaker for the stock that has the highest rank in the portfolio compared to the reference level. In contrast, the coefficient of the interaction term for the lowest-ranked stock ($Convexity \times$ *Rank: Last*) is negative in most columns of Table 9, indicating that the negative association between price convexity and the decision to sell is accentuated for lower-ranked stocks compared to the reference-level.

Despite the smaller number of observations in the subsamples employed, the results in Table 9 are largely consistent with the baseline findings, indicating that the asymmetry observed in the role of extrapolative expectations on the selling decisions based on ranks prevails even when all stocks in the portfolio have the same sign of return. Based on the above results, it is reasonable to conclude that the upward mobility bias exists independently of the salience of extreme ranks and the disposition effect.

3.7. *Portfolio-level outcome and upward mobility bias*

Research suggests that traders form mental accounts ignoring an integrative view of their portfolio, and their trading decisions are often influenced by individual asset characteristics (Barberis, 2018; Barberis & Huang, 2001). However, research also finds that the extent of influence of stock characteristics on certain trader behavior depends on portfolio-level outcomes as well. For example, An et al. (2024) argue that traders focus on both stock- and portfolio-level outcomes, and their stock-specific trading decisions also depend on the overall state of the portfolio. Specifically, they find that the disposition bias is almost non-existent when the portfolio is trading at a gain, however, it significantly impacts trading decisions when the overall portfolio is at a loss.

Given the evidence on the role of portfolio-level return on trading decisions, we examine whether upward mobility bias is impacted by portfolio returns. To test the same, we create two subsamples based on the portfolio level returns, one subsample where all trader-portfolios are at a gain and another where all are at a loss.

We present the results in Table 10. In line with the findings of An et al. (2024), we find that the coefficient of $Stock^+$ is positive only in columns (7)-(11) in Table 10, where the overall portfolio is at a loss, and is negative in columns (2)-(6) where the portfolio is at a gain. More importantly, we find strong evidence in support of upward mobility bias in both subsamples based on the overall portfolio return. Similar to the baseline analysis, we find that the magnitude of the negative association between price convexity and the selling decisions diminishes for stocks that have a higher return-rank compared to the reference level. At the reference level, price convexity has a negative and significant impact on selling decisions. The impact of price convexity on the selling decisions is significantly more negative for the lower-ranked stocks and is most negative for the lowest-ranked stock in the portfolio. For example, in column (3), the coefficient of the interaction term $Convexity \times$ *Rank: Last* is -0.076, indicating that compared to the reference-level stocks, one standard deviation increase in the price convexity reduces the selling propensity by an additional 7.6 percentage points for the last ranked stock in the portfolio. Overall, one standard deviation increase in the price convexity of the last-ranked stocks (column (3) of Table 10) lowers the selling propensity by 12.9% (-5.3 - 7.6). In most columns of Table 10, we find that the coefficient of *Rank: First* is positive, statistically significant, and in many cases reverses the negative association between price convexity and selling decisions of the stock compared to the reference rank.

Overall, we find that, unlike disposition bias, upward mobility bias is not dependent on portfolio performance. Regardless of the portfolio status, extrapolative expectations influence the trading in lower-ranked stocks to a significantly greater degree than the higher-ranked stocks.

3.8. Convexity based on one-month price movements

In all of our analyses, we measure convexity on the assumption that traders observe price path of a stock from the date of purchase. Consequently, our baseline price convexity measure at a point is specific to an investor-stock pair based on the prior holding period. However, traders may be observing price movements even before buying the stock. As an outcome, their future expectations and trading decisions could also be influenced by price movements prior to purchase. Hence, it is important to examine whether the heterogeneity in the association of convexity and the selling decisions based on return-ranks will hold if the convexity is measured with price data prior to the stock purchase.

By employing such a measure, we also ensure that on a particular stock-trading-day level, the value of price convexity for a stock is same across all traders in the sample, but the return-based rank of a stock will vary in each trader's portfolio, as in the previous estimations. Therefore, estimations with such a proxy will demonstrate how the selling propensity for each stock varies based on a stock's relative position in each trader's portfolio, despite all traders observing the same price path.

We capture the convexity of the price path based on closing prices over the previous 20 trading days, representing approximately one calendar month. Hence, even if a trader has been holding the stock within the portfolio for less than twenty trading days, the convexity measure is based on the previous 20 trading day price data. We then re-estimate the baseline specification with the modified price convexity measure and present the results in Table 11.

We find a similar pattern of results as in the baseline analysis, indicating that the phenomenon is most likely driven by the difference in the ranks of the stock within the portfolio. The findings reaffirm our claim that upward mobility bias is likely driving the mechanism behind the heterogeneous influence of extrapolative expectations on the selling decisions of traders, as the key variable of interest that varies across traders is the rank of the stock in each trader's portfolio.

4. Discussion of results

A possible alternative explanation for the results so far could be driven by trader expectations of mean reversion in the performance of portfolio stocks. However, our results point out that mean reversion is unlikely to be the primary factor driving the results. First, we observe a similar asymmetric pattern in the selling decisions of low- versus high-ranked stocks when there are no significant differences in the level of returns or extreme ranks stocks despite the variation in the return-rank of portfolio stocks. The result rule out mean reverting expectations as a potential mechanism, as mean reverting expectations would have led to similar trading decisions in stocks that have similar return levels.

Second, we find that the asymmetry in the association between convexity and selling propensity for low-ranked and high-ranked stocks remains largely true even in situations where all constituent stocks in the portfolio are in gains or losses. If mean reverting expectations were driving the decisions, then the association between price convexity and selling decisions would not vary based on the return ranks when all stocks in the portfolio have the same return sign.

Finally, we observe that the change in the ranks, without being accompanied by significant changes in prices, also exhibits outcomes similar to those observed for level ranks. Strong evidence in favor of ranks, despite trivial returns, suggests that upward mobility bias is the likely mechanism behind the asymmetric impact of extrapolative expectations on selling decisions.

Our results strongly resonate with earlier studies, which document that, while forecasting future performance, people expect a poorly performing entity (having a low rank) to improve in its performance more than those that are already performing well (having a high rank). In other words, people expect the performance of a low-ranked entity to improve to a greater degree than that of a high-ranked entity. Such a bias could result in suboptimal forecasts as traders will be overoptimistic about the performance of the lower ranked stocks in their portfolio.

The results also indicate that upward mobility bias is likely to contribute to the disposition effect. Furthermore, unlike the rank effect Hartzmark (2015), where traders are more likely to sell the highest and lowest ranked stocks, the influence of extrapolative expectations is greatest among the lowest ranked stocks and weakens with an increase in the return-rank. Therefore, our results also contribute to the understanding of both the disposition effect (Odean, 1998) and the rank effect (Hartzmark, 2015).

5. Robustness of the key results

5.1. Alternate measures of price convexity

In the baseline analysis, we implement a measure of price convexity based on the approach suggested by Gulen and Woeppel (2022). As a robustness check, we use two alternate measures of the price path. First, we compute the median value of $Convexity$ and construct an indicator variable that takes a value of 1 if the value of $Convexity$ is above the median value and zero otherwise. We present the results in Table A.1 and find that when the price convexity is above the median (*I(Above median Convexity)* $= 1$), the probability of selling a stock usually declines for the stock at the reference level rank. However, for stocks ranked lower relative to the reference rank, convexity leads to a greater reduction in the selling propensity. Broadly, the results in Table A.1 are consistent with the results of the baseline analysis.

Second, we employ an alternative measure of convexity as per Chen, Yu, and Wang (2018). Chen et al. (2018) measure of convexity by capturing the coefficient C_2 for each investor-stock-trading-day observation from the following regression.

$$P_{ijt} = \quad \alpha \ + C_1 \ Days_{ijt} \ + C_2 \ Days_{ijt}^2 \ + \epsilon_{ijt} \tag{3}$$

where P_{ijt} is the price of stock j in the portfolio of investor i as on trading day t. $Days_{ijt}$ is number of trading days since purchase of stock j by investor i as on day t. Higher the value of C_2, the greater the convexity in the experienced price path. We ensure a minimum of five observations within each trader-stock position to estimate the coefficients in Equation 3 and denote the measure of convexity computed as $Convexity\ (CYW)$.

They examine whether momentum profits are associated with acceleration or deceleration of prices, captured through C_2, after controlling for level returns. Although Chen et al. (2018) do not explicitly claim that their measure of convexity measures extrapolative expectations, the positive association between momentum returns and convexity is claimed to be linked to extrapolative bias.

In Table A.2, we document the variation in the influence of $Convexity\ (CYW)$ on the selling decisions with respect to the return ranks of the stocks. Similar to the baseline results, we find that the coefficient of $Convexity\ (CYW) \times$ *Rank: Last* is negative and significant in all the columns, and the coefficient of $Convexity\ (CYW) \times$ *Rank: First* is either positive or insignificant. The results in Table A.2 clearly highlight the fact that extrapolative expectations tend to lower the selling propensity in the lower-ranked stocks but not in the higher-ranked stocks in the portfolio.

5.2. *Alternative estimation approaches*

In all analyses so far, we have employed a linear probability model (LPM) to examine the influence of extrapolative expectations on the selling decisions of the traders. Although LPM is a popular model, it is not the only model that researchers use to study the trading behavior in financial markets. Two widely used alternative models are the Cox proportional risk model (Cox, 1972) and the Probit model. Both alternative models address one major drawback of the LPM that the predicted values in the LPM can lie outside the zero-to-one interval, which violates the axiom of probability theory.

5.2.1. *Cox proportional hazard model*

As an alternative, we employ the Cox proportional hazard estimation, which is defined below.

$$\begin{aligned} h_{i,j}(t|X(t)) =& h_0(t)\exp\{\beta_1\, Portfolio^{+}_{it} + \beta_2\, Stock^{+}{}_{ijt} + \\ & + \beta_3\, Convexity_{ijt} + \\ & \beta_4 \sqrt{Days}_{ijt} + \beta_5\, Volatility_{jt} + \\ & \beta_6\, Convexity_{ijt} \times \textit{Return Rank}_{ijt}\} \end{aligned} \tag{4}$$

$h_{i,j}(t|X(t))$ is the likelihood that stock j held by trader i is sold on trading day t given that the trader continued to remain invested up to day t. $h_0(t)$ is the conditional probability of selling when all independent variables are 0. The key difference between Cox proportional hazard model estimates and other models such as Probit and LPM is that Cox model estimates the conditional likelihood of selling while other models estimate the unconditional probability of selling.

We present the result in Table A.3 and find that the sign and significance of the coefficients are in line with the findings of the baseline analysis with LPM. However, the interpretation of the economic effect of the coefficients is different. For example, in column (3), the coefficient of $Convexity$ is -0.117 which implies that one standard deviation (SD) increase in price convexity lowers the conditional likelihood of selling by a factor of 0.89 (exp(-0.117)). Similarly, the coefficient of $Convexity \times$ *Rank: Last* is -0.205 in column (3), which implies that compared to the reference level, the selling propensity for the stock having the lowest rank in the portfolio is further reduced by a factor of 0.81 (exp(-0.205)) when the price convexity increases by one SD. Therefore, when the stock has the lowest rank in the portfolio, one SD increase in price convexity lowers the conditional likelihood of selling by a net factor of 0.72 (exp(-0.117 - 0.205)). Overall, the results from the hazard model also imply that the negative association between price convexity and selling decisions is greater for stocks that have a lower rank than the reference level and the opposite for stocks that have a higher rank than the reference level.

5.2.2. Probit model

The results of the estimation of a probit model are presented in Table A.4. Similar to LPM, the coefficients of a probit model have a direct interpretation in terms of an increase or a decrease in the unconditional probability. However, the major advantage of the probit model is that the predicted values satisfy the axioms of probability and will also lie in the range of zero to one. The disadvantage of probit model is that it is not linear, hence the impact of unobservable heterogeneities cannot be accounted for easily like in the case of LPM by adding fixed effects. The results in Table A.4 are again in line with the baseline findings, which implies that the phenomenon documented in the paper is not due to the choice of any specific estimation technique.

5.3. *Trading experience, investment level and demogrpahics*

5.3.1. *Self-reported trading experience*

For a subset of traders in our sample, we have data on self-reported trading experience ranging from 'no experience' to 'extensive experience.' We classify traders into two categories based on their trading experience, the first group represents traders with no or limited experience, and the second group with traders having 'good' or 'extensive' experience. The results are presented in Table A.5. In both groups, we examine the prevalence of upward mobility bias and find that extrapolative expectations lead to lower selling propensity in the lower-ranked stocks but the influence is dampened for the higher-ranked stocks. The results in Table A.5 suggest that upward mobility bias affects the trading decisions of experienced as well as less experienced traders.

5.3.2. *Trade intensity and investment amount*

We examine whether the influence of stock ranks is different for trader groups classified based on their trading intensity and investment amount. We measure the trading intensity by counting the total number of transactions carried out by the trader in the sample and categorize them into the above- and below-sample median groups. Similarly, traders are bifurcated into two groups on the basis of the median of the amount of money invested. We then re-estimate the baseline specification for all subsamples and present the results in Table A.6 for trading intensity and Table A.7 for the investment amount. In both the subsamples, we find that upward mobility bias significantly influences trading decisions and that the results indicate the same pattern as the baseline analysis.

5.3.3. Demographics

Similar to the information on the trading experience, the data set contains information on the age and gender of approximately 48% of the traders in the baseline sample. We examine whether the prevalence of upward mobility bias varies based on the age or gender of the traders in the sample. The final sample with complete demographic information has 10% female traders and approximately 90% male traders. We separately estimate the baseline model in the sample of male and female traders in Table A.8 and find strong evidence of upward mobility bias among male traders, but no evidence in the sample of female traders. Based on the analysis so far we are unable to explain why female traders are less prone to upward mobility bias than male traders, however, our results are similar to the findings of Barber and Odean (2001) who find that the trading decisions of female traders are less influenced by behavioral traits such as overconfidence. In Table A.9, we divide the baseline sample according to the age of the traders (below and above 50 years of age) and investigate the prevalence of upward mobility bias. Overall, we find that traders in both subsamples exhibit trading behavior in line with upward mobility bias and expect their lower-ranked stocks to rise more than their higher-ranked stocks.

5.4. *Extended sample analysis*

To arrive at our baseline sample, we considered only those trader-day observations in which the trader transacted at least once in any of their stocks in the portfolio and only included stock positions with a holding period of less than 100 days. In addition, we excluded any trader-stock observations where the nominal price of the stock was less than $5. To address the concern that the results in the baseline analysis are robust and do not depend on any particular sample, we carry out an extended sample analysis by selecting the entire available data. The results are presented in Table A.10. In line with the baseline results, we find that the negative impact of price convexity on selling decisions is more intense for lower-ranked stocks than higher-ranked stocks. Hence, we find that the phenomenon of upward mobility bias exists in the extended sample as well.

6. Conclusion

We examine the likely variation in the association of price path convexity with trader-level selling propensities for stocks that vary on their ranks in a portfolio based on their performance. Specifically, the research attempts to uncover whether the association between the likelihood of selling and the extrapolation of observed price path is related to the return-ranks of stocks in a portfolio. The proxy for the extrapolative behavior, which cannot be directly observed in the transaction-level data, is captured through the convexity of the price path. Price convexity is argued to capture extrapolative expectations through declining weights attached to more distant price changes.

Our key finding is that the negative association between price convexity and selling propensity is magnified for stocks that rank low on their performance relative to their high-ranked counterparts within a portfolio. Traders become more likely to sell a stock when its rank in the portfolio increases. The finding suggests that individual traders strongly believe that the relatively underperforming (low ranked) stocks will recover in the future when they observe a convex price path. The driving mechanism is unlikely to be the belief in mean reversion in the returns of stocks that have underperformed in the past. In this regard, we find that the asymmetry persists even when the difference in the level of returns does not vary significantly between the entire range of ranked stocks. Furthermore, the asymmetry in the association between convexity and selling propensity for the low-ranked and high-ranked stocks prevails in situations where all the stocks are gains or losses, indicating it is unlikely to be driven strongly by mean reversion. Finally, we find that an improvement (decline) in the rank of a stock from the previous trading day within a portfolio leads to a weaker impact of convexity on the selling propensity.

The role of ranks is absent when the stocks are ranked in alphabetical order, a static alternative criterion, implying that the pattern is present only when the ranks are linked to performance. The variation in the association between the selling propensity and extrapolative expectations captured by price convexity along the stock ranks is in line with the upward mobility bias documented in situations involving performance-based ranking of a set of objects. Under the argument of upward mobility bias, individuals assume the outperformance of low-ranked objects on account of a biased expectation in the improvement in their absolute performance. The paper, by uncovering the interaction between the rank of stocks in a portfolio and price convexity, contributes significantly to the literature on investor trading behavior.

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Table 1: Variable definitions

Variable Name	Description
$Sell_{ijt}$	1 if investor i sells stock j on day t, else 0
$h_{i,j}(t\|X(t))$	Probability of trader i to sell stock j on trading day t conditional on the trader remaining invested up to day t
$Portfolio^{+}_{it}$	1 if investor $i's$ net portfolio return on day t is positive, else 0
$Stock_{ijt}$	Investor $i's$ return in stock j on day t is positive than 1, else 0
$Convexity_{ijt}$	Convexity of the price path of the position of trader i in stock j from the start of the investment till trading day t, as per Equation 1 based on daily price changes.
$Convexity\ (CYW)_{ijt}$	Convexity of the price path of the position of trader i in stock j from the start of the investment till trading day t, as per Equation 3 based on methodology proposed by Chen et al. (2018)
$\sqrt{Days}_{ijt}$	Square root of number of trading days since purchase of stock j by investor i as on day t
$Volatility_{jt}$	Mean absolute value of daily return in the previous 250 trading days of stock j as computed on day t
Change in rank from t-1 to t	Change in the rank of the stock within the trader's portfolio compared to the previous day. For example, if the rank of a stock changes from six to five, it is coded as a positive change of +1. In contrast, if the rank of a stock changes from six to seven, it is coded as a negative change of -1.
I(1. Rank Improvement from t-1 to t)	1 if the rank of the stock within the portfolio increases compared to the previous day. For example, if the rank of a stock changes from six to five, it is coded as rank improvement.
I(2. Rank Decline from t-1 to t)	1 if the rank of the stock within the portfolio decreases compared to the previous day. For instance, if the rank of a stock changes from six to seven it is coded as rank decline.
P_{ijt}	Price of stock j in the portfolio of investor i as on trading day t
$\|Return_{ijt}\|$	Absolute value of price change of stock i in the portfolio of trader j on trading day t over the previous trading day.

This table contains a description of the variables employed in the analysis.

Table 2: Levels of return rank variable

Number of stocks in portfolio	Reference rank	Estimated ranks	
		Higher Ranks	Lower Ranks
Two	*Second*	*First*	-
$Three$	*Second*	*First*	*Last*
$Four$	*Second*	*First*	*Second Last*, *Last*
$Five$	*Third*	*First*, *Second*	*Second Last*, *Last*
$\geq Six$	*Third* to *Third Last*	*First*, *Second*	*Second Last*, *Last*

This table contains a description of the return rank variable. The reference level for the analyses presented in the subsequent tables is based on the number of stocks in the portfolio of the trader. The reported coefficients of the interaction term between $Convexity$ × *Return Rank* have to be interpreted with respect to the reference level.

Table 3: Summary statistics of variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$Sell\ Indicator_{ijt}(\%)$	423,242	23.44	42.36	0	0	0	100
$Portfolio_{it}^{+}(\%)$	423,242	54.11	49.83	0	0	100	100
$Stock_{ijt}^{+}$	423,242	54.29	49.82	0	0	100	100
$Convexity_{ijt}$	423,242	0.01	0.05	-0.16	-0.02	0.02	0.26
$\sqrt{Days}_{ijt}$	423,242	4.86	2.18	1.41	3.00	6.48	10.00
$Volatility_{jt}(\%)$	423,242	2.30	0.90	0.80	1.61	2.86	6.05
Number of stocks in the portfolio	423,242	7.48	8.41	2	3	9	121

This table provides summary statistics for the variables employed in the multivariate analysis. All the indicator variables are multiplied by 100 to express the summary statistics in percentage. The variable definitions are provided in Table 1 and Table 2.

Table 4: Variation in the influence of $Convexity$ on selling decision of stocks with respect to return-ranks

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^+$	−0.239***	−0.115***	−0.081***	−0.045***	−0.029***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.005)
$Stock^+$	0.241***	0.116***	0.097***	0.055***	0.030***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.007)
$Convexity$	−0.089***	−0.040***	−0.021**	−0.038***	−0.029***
	(0.007)	(0.008)	(0.009)	(0.013)	(0.004)
$\sqrt{Days}$	0.187***	0.168***	0.141***	0.123***	0.087***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.004)
$Volatility$	0.340***	0.309***	0.209***	0.177***	0.163***
	(0.052)	(0.059)	(0.064)	(0.064)	(0.028)
$Convexity$ × *Rank: First*	0.085***	0.050***	0.023**	0.064***	0.036***
	(0.008)	(0.010)	(0.010)	(0.016)	(0.006)
$Convexity$ × *Rank: Second*				−0.008	0.024***
				(0.015)	(0.006)
$Convexity$ × *Rank: Second Last*			−0.058***	−0.037**	−0.024***
			(0.011)	(0.015)	(0.005)
$Convexity$ × *Rank: Last*		−0.063***	−0.060***	−0.050***	−0.041***
		(0.010)	(0.013)	(0.015)	(0.006)
Trader FE	Yes	Yes	Yes	Yes	Yes
Rank FE	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	76,109	65,515	52,152	41,189	188,277
Adjusted R^2	0.182	0.186	0.189	0.228	0.216

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5: Variation in the influence of $Convexity$ on selling propensity with ranks: Return difference between the highest and low
rank stock

Number of Stocks in the portfolio	$R_{first} - R_{last}$ *below average*					$R_{first} - R_{last}$ *above average*				
	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Portfolio^{+}$	−0.243***	−0.118***	−0.080***	−0.030**	−0.031***	−0.164***	−0.161***	−0.099***	−0.067***	−0.031
	(0.010)	(0.012)	(0.012)	(0.015)	(0.005)	(0.023)	(0.019)	(0.019)	(0.021)	(0.00
$Stock^{+}$	0.249***	0.130***	0.099***	0.049***	0.041***	0.188***	0.091***	0.069***	0.041*	0.01
	(0.013)	(0.013)	(0.016)	(0.014)	(0.009)	(0.026)	(0.020)	(0.019)	(0.022)	(0.00
$Convexity$	−0.085***	−0.039***	−0.028**	−0.058***	−0.037***	−0.123***	−0.037**	−0.015	−0.044**	−0.023
	(0.009)	(0.012)	(0.013)	(0.022)	(0.005)	(0.017)	(0.015)	(0.019)	(0.022)	(0.00
$\sqrt{Days}$	0.200***	0.168***	0.152***	0.150***	0.099***	0.134***	0.139***	0.104***	0.071***	0.067
	(0.007)	(0.008)	(0.011)	(0.012)	(0.005)	(0.017)	(0.014)	(0.016)	(0.019)	(0.00
$Volatility$	0.391***	0.295***	0.333***	0.119	0.138***	0.347***	0.378***	0.027	0.240**	0.159
	(0.080)	(0.080)	(0.093)	(0.103)	(0.038)	(0.106)	(0.137)	(0.085)	(0.115)	(0.0
$Convexity \times$ *Rank: First*	0.068***	0.059***	0.033*	0.083***	0.061***	0.179***	0.039**	0.006	0.061**	0.021
	(0.011)	(0.014)	(0.017)	(0.028)	(0.009)	(0.021)	(0.019)	(0.020)	(0.024)	(0.00
$Convexity \times$ *Rank: Second*				0.024	0.033***				−0.020	0.02
				(0.026)	(0.008)				(0.024)	(0.00
$Convexity \times$ *Rank: Second Last*			−0.067***	−0.023	−0.031***			−0.070**	−0.064**	−0.0
			(0.016)	(0.025)	(0.007)			(0.028)	(0.026)	(0.00
$Convexity \times$ *Rank: Last*		−0.081***	−0.074***	−0.053**	−0.044***		−0.082***	−0.055**	−0.030	−0.035
		(0.014)	(0.020)	(0.025)	(0.009)		(0.019)	(0.026)	(0.026)	(0.00
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	52,867	40,626	31,392	24,487	108,702	23,242	24,889	20,760	16,702	79,5
Adjusted R^2	0.195	0.228	0.215	0.255	0.228	0.122	0.223	0.271	0.341	0.3

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table 6: Variation in the influence of $Convexity$ on selling propensity with ranks: Change in the return-rank

Number of Stocks in the portfolio	$\|Return_{ijt}\|$ *below average*					$\|Return_{ijt}\|$ *above average*				
	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
$Portfolio^{+}$	−0.215***	−0.090***	−0.057***	−0.021**	−0.017***	−0.315***	−0.193***	−0.285***	−0.251***	−0.0
	(0.011)	(0.008)	(0.010)	(0.010)	(0.005)	(0.057)	(0.049)	(0.058)	(0.069)	(0.
$Stock^{+}$	0.167***	0.059***	0.044***	0.023**	0.006	0.153*	0.252***	0.291***	0.125*	0.05
	(0.011)	(0.010)	(0.010)	(0.011)	(0.007)	(0.079)	(0.044)	(0.060)	(0.072)	(0.
$Convexity$	−0.049***	−0.042***	−0.042***	−0.047***	−0.029***	−0.060	−0.053**	−0.067**	−0.047	−0.0
	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)	(0.036)	(0.027)	(0.032)	(0.039)	(0.
$\sqrt{Days}$	0.179***	0.171***	0.134***	0.132***	0.094***	0.062	0.125***	0.087	0.135**	0.06
	(0.006)	(0.007)	(0.008)	(0.009)	(0.004)	(0.039)	(0.033)	(0.057)	(0.053)	(0.
$Volatility$	0.207***	0.294***	0.084	0.174**	0.166***	0.492	0.285	0.490	0.639*	0.23
	(0.063)	(0.070)	(0.062)	(0.076)	(0.034)	(0.435)	(0.285)	(0.402)	(0.361)	(0.
$Convexity$ × *Change in rank from t-1 to t*	0.048***	0.029***	0.015**	0.019***	0.002*	−0.026	0.013	0.022	−0.009	0.01
	(0.011)	(0.007)	(0.007)	(0.006)	(0.001)	(0.043)	(0.023)	(0.029)	(0.020)	(0.
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Change in rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	62,324	53,624	42,719	33,810	140,926	13,785	11,891	9,433	7,379	47
Adjusted R^2	0.212	0.211	0.209	0.250	0.237	0.410	0.464	0.309	0.488	0

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and dat fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1% and 10% levels, respectively.

Table 7: Variation in the influence of $Convexity$ on selling propensity with ranks: Increase/Decrease in the return-rank

Number of Stocks in the portfolio	$\|Return_{ijt}\|$ *below average*					$\|Return_{ijt}\|$ *above average*				
	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
$Portfolio^{+}$	−0.215***	−0.090***	−0.057***	−0.021**	−0.021***	−0.311***	−0.194***	−0.280***	−0.259***	−0.0
	(0.011)	(0.008)	(0.010)	(0.010)	(0.005)	(0.057)	(0.050)	(0.056)	(0.068)	(0.
$Stock^{+}$	0.167***	0.059***	0.044***	0.024**	0.010	0.163**	0.248***	0.291***	0.093	0.05
	(0.011)	(0.010)	(0.010)	(0.011)	(0.008)	(0.078)	(0.044)	(0.059)	(0.072)	(0.
$Convexity$	−0.044***	−0.035***	−0.035***	−0.043***	−0.027***	−0.057	−0.033	−0.054	−0.077	−0.0
	(0.007)	(0.007)	(0.008)	(0.009)	(0.004)	(0.037)	(0.027)	(0.035)	(0.047)	(0.
$\sqrt{Days}$	0.179***	0.171***	0.134***	0.132***	0.094***	0.062	0.136***	0.093*	0.152***	0.06
	(0.006)	(0.007)	(0.008)	(0.009)	(0.004)	(0.039)	(0.032)	(0.054)	(0.055)	(0.
$Volatility$	0.205***	0.292***	0.085	0.173**	0.159***	0.462	0.311	0.584	0.669*	0.26
	(0.063)	(0.070)	(0.061)	(0.076)	(0.033)	(0.436)	(0.300)	(0.408)	(0.404)	(0.
$Convexity \times$ *I(1. Rank Improvement from t-1 to t)*	−0.017	−0.019	−0.023	−0.0004	−0.002	−0.051	−0.050	−0.021	0.029	0.03
	(0.022)	(0.018)	(0.020)	(0.018)	(0.005)	(0.067)	(0.044)	(0.045)	(0.039)	(0.
$Convexity \times$ *I(2. Rank Decline from t-1 to t)*	−0.069***	−0.051***	−0.037***	−0.033***	−0.009**	−0.008	−0.042	0.001	0.034	−0.0
	(0.011)	(0.009)	(0.011)	(0.011)	(0.004)	(0.061)	(0.050)	(0.056)	(0.059)	(0.
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Rank Change direction FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	62,324	53,624	42,719	33,810	154,006	13,785	11,891	9,433	7,379	34
Adjusted R^2	0.212	0.211	0.210	0.250	0.229	0.411	0.462	0.305	0.465	0

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and dat fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1% and 10% levels, respectively.

Table 8: Variation in the influence of $Convexity$ on selling propensity with alphabetical ranks

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^+$	−0.242***	−0.114***	−0.079***	−0.045***	−0.029***
	(0.009)	(0.007)	(0.008)	(0.010)	(0.005)
$Stock^+$	0.260***	0.119***	0.089***	0.058***	0.029***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
$Convexity$	−0.041***	−0.034***	−0.026***	−0.037***	−0.025***
	(0.006)	(0.007)	(0.009)	(0.010)	(0.004)
$\sqrt{Days}$	0.190***	0.175***	0.146***	0.132***	0.098***
	(0.005)	(0.006)	(0.008)	(0.007)	(0.004)
$Volatility$	0.365***	0.347***	0.235***	0.222***	0.205***
	(0.054)	(0.062)	(0.067)	(0.065)	(0.030)
$Convexity \times$ *Alphabetical Rank: First*	0.004	−0.003	−0.017	0.014	−0.003
	(0.008)	(0.010)	(0.011)	(0.014)	(0.006)
$Convexity \times$ *Alphabetical Rank: Second*				−0.005	−0.005
				(0.014)	(0.006)
$Convexity \times$ *Alphabetical Rank: Second Last*			−0.060***	−0.030*	−0.023***
			(0.012)	(0.017)	(0.006)
$Convexity \times$ *Alphabetical Rank: Last*		−0.015	−0.009	0.015	−0.002
		(0.009)	(0.012)	(0.016)	(0.007)
Trader FE	Yes	Yes	Yes	Yes	Yes
Alphabetical Rank FE	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	76,109	65,515	52,152	41,189	188,277
Adjusted R^2	0.178	0.180	0.186	0.220	0.208

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9: Variation in the influence of $Convexity$ on selling propensity with ranks: Portfolios with all stocks in gains and all in loss

	All stocks gains					*All stocks in losses*				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Convexity$	−0.078***	−0.056***	−0.045*	−0.018	−0.014	−0.060***	−0.058**	−0.080	−0.108*	−0.03
	(0.015)	(0.016)	(0.024)	(0.036)	(0.015)	(0.014)	(0.024)	(0.051)	(0.061)	(0.0
$\sqrt{Days}$	0.220***	0.201***	0.167***	0.060	0.049***	0.225***	0.134***	0.087*	0.181***	0.111
	(0.011)	(0.015)	(0.027)	(0.053)	(0.016)	(0.019)	(0.020)	(0.049)	(0.054)	(0.0
$Volatility$	0.556***	0.487***	0.752***	0.569*	0.151	0.271*	0.218*	0.188	0.657**	−0.1
	(0.115)	(0.120)	(0.225)	(0.296)	(0.092)	(0.161)	(0.123)	(0.177)	(0.294)	(0.1
$Convexity$ × *Rank: First*	0.047***	0.062***	−0.014	0.101**	0.026	0.059**	−0.061*	0.150*	0.143**	0.0
	(0.014)	(0.015)	(0.025)	(0.042)	(0.018)	(0.024)	(0.037)	(0.081)	(0.064)	(0.0
$Convexity$ × *Rank: Second*				−0.040	0.020				0.018	−0.0
				(0.040)	(0.016)				(0.047)	(0.0
$Convexity$ × *Rank: Second Last*			−0.039	0.001	−0.013			−0.044	−0.006	−0.05
			(0.032)	(0.046)	(0.028)			(0.061)	(0.054)	(0.0
$Convexity$ × *Rank: Last*		−0.060**	−0.014	−0.003	−0.111**		−0.031	0.022	−0.113*	−0.0
		(0.027)	(0.062)	(0.091)	(0.056)		(0.028)	(0.055)	(0.058)	(0.0
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	38,093	24,807	15,388	9,273	16,997	22,362	14,569	8,900	5,483	11,2
Adjusted R^2	0.137	0.227	0.264	0.353	0.381	0.309	0.335	0.382	0.474	0.4

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table 10: Variation in the influence of $Convexity$ on selling propensity with ranks: Portfolio in gains versus losses

Number of Stocks in the portfolio	*Portfolio in gain*					*Portfolio in loss*				
	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Stock^+$	−0.199***	−0.070***	−0.035**	−0.047***	−0.012***	0.447***	0.235***	0.168***	0.122***	0.079
	(0.020)	(0.017)	(0.017)	(0.016)	(0.004)	(0.014)	(0.014)	(0.018)	(0.019)	(0.0
$Convexity$	−0.088***	−0.053***	−0.046***	−0.017	−0.026***	−0.073***	−0.031**	−0.028*	−0.051***	−0.026
	(0.013)	(0.013)	(0.016)	(0.019)	(0.004)	(0.009)	(0.013)	(0.017)	(0.019)	(0.00
$\sqrt{Days}$	0.198***	0.184***	0.127***	0.104***	0.084***	0.158***	0.158***	0.162***	0.146***	0.102
	(0.011)	(0.010)	(0.013)	(0.014)	(0.005)	(0.008)	(0.011)	(0.012)	(0.014)	(0.00
$Volatility$	0.372***	0.416***	0.437***	0.288***	0.222***	0.182**	0.158**	0.123	0.207*	0.119
	(0.112)	(0.091)	(0.115)	(0.097)	(0.048)	(0.081)	(0.075)	(0.092)	(0.126)	(0.0
$Convexity$ × *Rank: First*	0.088***	0.056***	0.018	0.044**	0.024***	0.062***	0.071***	0.077***	0.103***	0.077
	(0.015)	(0.015)	(0.017)	(0.022)	(0.006)	(0.010)	(0.018)	(0.020)	(0.025)	(0.0
$Convexity$ × *Rank: Second*				−0.007	0.014**				−0.010	0.044
				(0.023)	(0.006)				(0.024)	(0.00
$Convexity$ × *Rank: Second Last*			−0.052***	−0.050**	−0.039***			−0.048**	−0.003	−0.0
			(0.017)	(0.023)	(0.008)			(0.022)	(0.021)	(0.00
$Convexity$ × *Rank: Last*		−0.076***	−0.089***	−0.117***	−0.069***		−0.048***	−0.021	−0.032	−0.01
		(0.017)	(0.022)	(0.024)	(0.009)		(0.015)	(0.021)	(0.022)	(0.00
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	36,069	33,929	27,950	22,365	108,703	40,040	31,586	24,202	18,824	79,5
Adjusted R^2	0.175	0.220	0.215	0.303	0.269	0.428	0.342	0.347	0.365	0.3

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table 11: Variation in the influence of Convexity on selling propensity with ranks: $Convexity$ based on prior 20 trading days

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^{+}$	-0.242^{***}	-0.115^{***}	-0.082^{***}	-0.047^{***}	-0.029^{***}
	(0.010)	(0.008)	(0.008)	(0.010)	(0.005)
$Stock^{+}$	0.237^{***}	0.115^{***}	0.094^{***}	0.054^{***}	0.030^{***}
	(0.011)	(0.010)	(0.011)	(0.011)	(0.007)
$Convexity$	-0.013^{***}	-0.009^{*}	0.010^{*}	0.002	-0.005^{***}
	(0.004)	(0.005)	(0.005)	(0.007)	(0.001)
$\sqrt{Days}$	0.183^{***}	0.167^{***}	0.139^{***}	0.124^{***}	0.088^{***}
	(0.005)	(0.006)	(0.007)	(0.008)	(0.004)
$Volatility$	0.379^{***}	0.428^{***}	0.229^{***}	0.268^{***}	0.210^{***}
	(0.072)	(0.067)	(0.078)	(0.077)	(0.034)
$Convexity \times$ *Rank: First*	0.039^{***}	0.028^{***}	0.015^{**}	0.035^{***}	0.028^{***}
	(0.005)	(0.006)	(0.007)	(0.009)	(0.003)
$Convexity \times$ *Rank: Second*				0.012	0.010^{***}
				(0.008)	(0.003)
$Convexity \times$ *Rank: Second Last*			-0.020^{***}	-0.024^{***}	-0.013^{***}
			(0.007)	(0.008)	(0.003)
$Convexity \times$ *Rank: Last*		-0.026^{***}	-0.035^{***}	-0.027^{***}	-0.025^{***}
		(0.007)	(0.007)	(0.008)	(0.004)
Trader FE	Yes	Yes	Yes	Yes	Yes
Rank FE	Yes	Yes	Yes	Yes	Yes
Stock $\times$ Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	75,586	65,124	51,832	40,961	187,634
Adjusted R^2	0.179	0.183	0.187	0.225	0.215

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock $\times$ year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Appendix

Table A.1: Variation in the influence of above median $Convexity$ on selling propensity with ranks

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^+$	−0.240***	−0.115***	−0.082***	−0.046***	−0.029***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.005)
$Stock^+$	0.241***	0.116***	0.098***	0.056***	0.030***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.007)
I(Above median Convexity)	−0.086***	−0.026***	−0.020*	−0.023*	−0.017***
	(0.009)	(0.010)	(0.011)	(0.013)	(0.003)
$\sqrt{Days}$	0.185***	0.168***	0.142***	0.121***	0.087***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.004)
$Volatility$	0.336***	0.308***	0.200***	0.181***	0.167***
	(0.052)	(0.059)	(0.065)	(0.064)	(0.029)
I(Above median Convexity) × *Rank: First*	0.106***	0.049***	0.024	0.080***	0.036***
	(0.011)	(0.012)	(0.017)	(0.020)	(0.008)
I(Above median Convexity) × *Rank: Second*				0.003	0.018***
				(0.017)	(0.006)
I(Above median Convexity) × *Rank: Second Last*			−0.055***	−0.026	−0.024***
			(0.014)	(0.017)	(0.006)
I(Above median Convexity) × *Rank: Last*		−0.067***	−0.076***	−0.058***	−0.061***
		(0.013)	(0.017)	(0.019)	(0.009)
Trader FE	Yes	Yes	Yes	Yes	Yes
Rank FE	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	76,109	65,515	52,152	41,189	188,277
Adjusted R^2	0.180	0.182	0.188	0.225	0.214

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2 The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table A.2: Variation in the influence of Alternative $Convexity$ proxy on selling propensity with ranks

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^{+}$	−0.243***	−0.120***	−0.088***	−0.046***	−0.030***
	(0.010)	(0.009)	(0.009)	(0.010)	(0.005)
$Stock^{+}$	0.240***	0.104***	0.089***	0.057***	0.023***
	(0.012)	(0.011)	(0.013)	(0.012)	(0.006)
$Convexity\ (CYW)$	−0.019***	−0.008**	0.007**	0.001	−0.002***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.001)
$\sqrt{Days}$	0.190***	0.182***	0.152***	0.133***	0.094***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.004)
$Volatility$	0.449***	0.432***	0.182**	0.185**	0.216***
	(0.071)	(0.069)	(0.076)	(0.074)	(0.035)
$Convexity\ (CYW) \times$ *Rank: First*	0.025***	0.015***	0.0004	0.012*	0.011***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)
$Convexity\ (CYW) \times$ *Rank: Second*				0.006	0.005**
				(0.006)	(0.002)
$Convexity\ (CYW) \times$ *Rank: Second Last*			−0.021***	−0.005	−0.004**
			(0.005)	(0.005)	(0.002)
$Convexity\ (CYW) \times$ *Rank: Last*		−0.013***	−0.017***	−0.010*	−0.011***
		(0.005)	(0.006)	(0.006)	(0.003)
Trader FE	Yes	Yes	Yes	Yes	Yes
Return Rank FE	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	67,092	57,622	46,027	36,580	168,430
Adjusted R^2	0.180	0.193	0.207	0.246	0.229

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table A.3: Variation in the influence of Convexity on selling propensity with ranks: Cox Proportional Hazard Model

Dependent Variable: Number of Stocks in the portfolio	*Cox Proportional Hazard* $h_{i,j}(t\|X(t))$				
	Two	$Three$	$Four$	$Five$	$> Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^+$	−0.839*** (0.013)	−0.511*** (0.016)	−0.386*** (0.020)	−0.280*** (0.024)	−0.337*** (0.014)
$Stock^+$	0.787*** (0.016)	0.490*** (0.022)	0.378*** (0.028)	0.327*** (0.036)	0.143** (0.019)
$Convexity$	−0.213*** (0.011)	−0.117*** (0.019)	−0.053* (0.025)	−0.177*** (0.042)	−0.219*** (0.015)
Rank: First	0.058*** (0.014)	0.242*** (0.019)	0.243*** (0.025)	0.397*** (0.039)	0.814*** (0.021)
Rank: Second				0.093** (0.040)	0.483*** (0.022)
Rank: Second Last			−0.009 (0.030)	0.051 (0.044)	0.497*** (0.025)
Rank: Last		0.220*** (0.021)	0.253*** (0.033)	0.443*** (0.043)	0.904*** (0.023)
$Volatility$	0.053*** (0.006)	0.051*** (0.008)	0.051*** (0.010)	0.069*** (0.013)	−0.005 (0.008)
$Convexity$ × *Rank: First*	0.248*** (0.013)	0.187*** (0.022)	0.091*** (0.031)	0.289*** (0.047)	0.279*** (0.022)
$Convexity$ × *Rank: Second*				0.072 (0.055)	0.215*** (0.028)
$Convexity$ × *Rank: Second Last*			−0.188*** (0.038)	−0.120* (0.058)	−0.079* (0.030)
$Convexity$ × *Rank: Last*		−0.205*** (0.025)	−0.262*** (0.034)	−0.100* (0.050)	−0.072** (0.023)
Observations	76,109	65,515	52,152	41,189	188,277
Max. Possible R^2	0.997	0.982	0.952	0.909	0.843

The dependent variable is the probability of investor i to sell stock j on day t conditional on the stock not being sold until trading day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. The coefficients are estimated from Cox proportional hazard model (Cox, 1972) described in Equation 4. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table A.4: Variation in the influence of Convexity on selling propensity with ranks: Probit Model

	Probit				
Dependent Variable:	$h_{i,j}(t\|X(t))$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$> Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^+$	-0.648^{***}	-0.349^{***}	-0.249^{***}	-0.176^{***}	-0.203^{***}
	(0.011)	(0.012)	(0.014)	(0.016)	(0.008)
$Stock^+$	0.594^{***}	0.327^{***}	0.235^{***}	0.199^{***}	0.082^{***}
	(0.014)	(0.016)	(0.019)	(0.023)	(0.011)
$Convexity$	-0.190^{***}	-0.093^{***}	-0.043^{**}	-0.104^{***}	-0.128^{***}
	(0.009)	(0.014)	(0.018)	(0.026)	(0.008)
Rank: First	0.047^{***}	0.191^{***}	0.178^{***}	0.272^{***}	0.488^{***}
	(0.012)	(0.014)	(0.017)	(0.025)	(0.012)
Rank: Second				0.064^{***}	0.271^{***}
				(0.025)	(0.013)
Rank: Second Last			0.0001	0.043	0.279^{***}
			(0.019)	(0.026)	(0.014)
Rank: Last		0.172^{***}	0.182^{***}	0.298^{***}	0.533^{***}
		(0.015)	(0.022)	(0.027)	(0.014)
$\sqrt{Days}$	0.377^{***}	0.354^{***}	0.331^{***}	0.306^{***}	0.259^{***}
	(0.007)	(0.007)	(0.009)	(0.010)	(0.006)
$Volatility$	0.055^{***}	0.042^{***}	0.041^{***}	0.051^{***}	0.002
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)
$Convexity \times$ *Rank: First*	0.243^{***}	0.162^{***}	0.081^{***}	0.200^{***}	0.180^{***}
	(0.012)	(0.017)	(0.022)	(0.031)	(0.014)
$Convexity \times$ *Rank: Second*				0.042	0.124^{***}
				(0.035)	(0.017)
$Convexity \times$ *Rank: Second Last*			-0.123^{***}	-0.090^{**}	-0.051^{***}
			(0.026)	(0.037)	(0.018)
$Convexity \times$ *Rank: Last*		-0.154^{***}	-0.188^{***}	-0.092^{***}	-0.070^{***}
		(0.019)	(0.024)	(0.033)	(0.014)
Constant	0.055^{***}	-0.405^{***}	-0.593^{***}	-0.824^{***}	-1.138^{***}
	(0.009)	(0.014)	(0.019)	(0.022)	(0.009)
Observations	76,109	65,515	52,152	41,189	188,277
Akaike Inf. Crit.	96,039.500	76,921.400	55,412.270	39,458.300	133,138.000

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table A.5: Variation in the influence of $Convexity$ on selling propensity with ranks and Trader experience

	Limited or No Experience					*Good or Extensive Experience*				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
$Portfolio^{+}$	−0.268***	−0.188***	−0.191***	−0.166***	−0.034**	−0.226***	−0.110***	−0.070***	−0.056***	−0.0
	(0.031)	(0.031)	(0.052)	(0.062)	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0
$Stock^{+}$	0.201***	0.160***	0.087*	0.144***	0.017	0.241***	0.136***	0.098***	0.067***	0.0
	(0.042)	(0.037)	(0.048)	(0.040)	(0.013)	(0.018)	(0.016)	(0.018)	(0.016)	(0
$Convexity$	−0.110***	−0.083**	−0.047	−0.094*	−0.037**	−0.087***	−0.057***	−0.051***	−0.041**	−0.0
	(0.033)	(0.032)	(0.046)	(0.048)	(0.016)	(0.012)	(0.014)	(0.016)	(0.021)	(0
$\sqrt{Days}$	0.206***	0.117***	0.134***	0.076**	0.105***	0.207***	0.193***	0.165***	0.126***	0.0
	(0.036)	(0.035)	(0.048)	(0.031)	(0.013)	(0.010)	(0.012)	(0.013)	(0.016)	(0
$Volatility$	0.200	0.621***	0.124	0.537	0.231***	0.299***	0.451***	0.500***	0.324**	0.1
	(0.202)	(0.230)	(0.350)	(0.365)	(0.080)	(0.105)	(0.103)	(0.121)	(0.130)	(0
$Convexity$ × *Rank: First*	0.115***	0.084**	0.049	0.113*	0.064***	0.086***	0.048***	0.026	0.033	0.0
	(0.035)	(0.034)	(0.050)	(0.058)	(0.014)	(0.015)	(0.017)	(0.017)	(0.025)	(0
$Convexity$ × *Rank: Second*				0.009	0.043***				−0.022	0.0
				(0.070)	(0.015)				(0.022)	(0
$Convexity$ × *Rank: Second Last*			−0.137**	−0.077*	−0.059***			−0.016	−0.009	−0.0
			(0.055)	(0.042)	(0.012)			(0.017)	(0.025)	(0
$Convexity$ × *Rank: Last*		−0.069**	−0.048	−0.090	−0.040**		−0.055***	−0.038*	−0.064**	−0.0
		(0.035)	(0.067)	(0.057)	(0.018)		(0.018)	(0.021)	(0.026)	(0
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Return Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	10,266	8,803	6,668	5,180	21,773	28,847	26,182	21,868	17,662	9
Adjusted R^2	0.297	0.388	0.377	0.385	0.370	0.233	0.233	0.229	0.316	

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-mon and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate st significance at 1%, 5%, and 10% levels, respectively.

Table A.6: Variation in the influence of $Convexity$ on selling propensity with ranks and trading intensity

	Below median trading intensity					*Above median trading intensity*				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Portfolio^{+}$	−0.260***	−0.128***	−0.104***	−0.051***	−0.034***	−0.224***	−0.112***	−0.076***	−0.028**	−0.028
	(0.014)	(0.012)	(0.017)	(0.019)	(0.007)	(0.011)	(0.010)	(0.012)	(0.014)	(0.00
$Stock^{+}$	0.224***	0.099***	0.054***	0.040**	0.010*	0.250***	0.128***	0.113***	0.038***	0.043
	(0.017)	(0.016)	(0.016)	(0.016)	(0.006)	(0.013)	(0.013)	(0.016)	(0.015)	(0.0
$Convexity$	−0.077***	−0.061***	−0.030**	−0.071***	−0.020***	−0.098***	−0.031**	−0.018	−0.030	−0.043
	(0.011)	(0.013)	(0.015)	(0.017)	(0.004)	(0.010)	(0.012)	(0.014)	(0.022)	(0.00
$\sqrt{Days}$	0.256***	0.224***	0.165***	0.146***	0.106***	0.162***	0.140***	0.130***	0.108***	0.075
	(0.011)	(0.011)	(0.013)	(0.016)	(0.006)	(0.008)	(0.009)	(0.012)	(0.014)	(0.00
$Volatility$	0.298***	0.190**	0.296***	0.164*	0.217***	0.315***	0.302***	0.109	0.170**	0.115
	(0.080)	(0.079)	(0.099)	(0.099)	(0.035)	(0.073)	(0.087)	(0.073)	(0.070)	(0.0
$Convexity$ × *Rank: First*	0.077***	0.045***	0.038**	0.095***	0.025***	0.080***	0.052***	0.015	0.048**	0.046
	(0.013)	(0.015)	(0.016)	(0.022)	(0.008)	(0.012)	(0.015)	(0.016)	(0.024)	(0.00
$Convexity$ × *Rank: Second*				0.023	0.022***				−0.027	0.024
				(0.023)	(0.007)				(0.023)	(0.00
$Convexity$ × *Rank: Second Last*			−0.043**	−0.012	−0.019**			−0.056***	−0.049**	−0.031
			(0.018)	(0.019)	(0.008)			(0.018)	(0.023)	(0.00
$Convexity$ × *Rank: Last*		−0.042***	−0.032	−0.032	−0.052***		−0.102***	−0.071***	−0.076***	−0.038
		(0.014)	(0.021)	(0.022)	(0.008)		(0.015)	(0.019)	(0.025)	(0.00
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Return Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	38,207	32,767	26,251	20,611	94,194	37,902	32,748	25,901	20,578	94,0
Adjusted R^2	0.214	0.227	0.264	0.293	0.287	0.206	0.216	0.208	0.274	0.2

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table A.7: Variation in the influence of $Convexity$ on selling propensity with ranks and investment amount

	Below median investment					*Above median investment*				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Portfolio^{+}$	−0.174***	−0.062***	−0.054***	0.002	−0.007	−0.287***	−0.151***	−0.111***	−0.093***	−0.050
	(0.014)	(0.011)	(0.012)	(0.014)	(0.006)	(0.012)	(0.011)	(0.012)	(0.014)	(0.00
$Stock^{+}$	0.127***	0.006	0.055***	0.022	−0.001	0.323***	0.204***	0.131***	0.085***	0.058
	(0.017)	(0.016)	(0.017)	(0.017)	(0.005)	(0.014)	(0.014)	(0.017)	(0.015)	(0.0
$Convexity$	−0.111***	−0.062***	−0.051***	−0.072***	−0.024***	−0.092***	−0.046***	−0.039**	−0.046**	−0.041
	(0.011)	(0.013)	(0.016)	(0.018)	(0.004)	(0.011)	(0.012)	(0.015)	(0.020)	(0.00
$\sqrt{Days}$	0.268***	0.263***	0.183***	0.167***	0.105***	0.169***	0.149***	0.136***	0.119***	0.087
	(0.010)	(0.011)	(0.013)	(0.014)	(0.006)	(0.009)	(0.009)	(0.013)	(0.013)	(0.00
$Volatility$	0.344***	0.262**	0.198*	0.229*	0.167***	0.293***	0.297***	0.237***	0.167**	0.161
	(0.076)	(0.102)	(0.114)	(0.130)	(0.032)	(0.079)	(0.096)	(0.081)	(0.074)	(0.0
$Convexity \times$ *Rank: First*	0.105***	0.048***	0.036**	0.100***	0.020***	0.089***	0.065***	0.049***	0.057**	0.051
	(0.013)	(0.015)	(0.018)	(0.023)	(0.008)	(0.014)	(0.013)	(0.016)	(0.024)	(0.00
$Convexity \times$ *Rank: Second*				0.0005	0.013*				−0.016	0.031
				(0.023)	(0.008)				(0.022)	(0.00
$Convexity \times$ *Rank: Second Last*			−0.036*	−0.042**	−0.015*			−0.053***	−0.010	−0.035
			(0.020)	(0.019)	(0.008)			(0.018)	(0.025)	(0.00
$Convexity \times$ *Rank: Last*		−0.051***	−0.025	−0.063***	−0.046***		−0.069***	−0.060***	−0.062**	−0.040
		(0.014)	(0.023)	(0.023)	(0.008)		(0.015)	(0.020)	(0.026)	(0.00
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Return Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	38,045	32,751	26,174	20,669	94,634	38,031	32,732	25,948	20,495	93,4
Adjusted R^2	0.264	0.278	0.283	0.341	0.308	0.227	0.227	0.232	0.268	0.2

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table A.8: Variation in the influence of $Convexity$ on selling propensity with ranks and trader gender

Number of Stocks in the portfolio	*Male*					*Female*				
	Two	$Three$	$Four$	$Five$	$\geq Six$	Two	$Three$	$Four$	$Five$	$\geq S$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(1
$Portfolio^{+}$	−0.252***	−0.117***	−0.087***	−0.062***	−0.036***	−0.693***	−0.362**	0.176**		−0.07
	(0.013)	(0.012)	(0.014)	(0.019)	(0.008)	(0.217)	(0.142)	(0.081)	(0.000)	(0.04
$Stock^{+}$	0.226***	0.088***	0.099***	0.062***	0.031***	0.116	−0.096	0.180	0.060	0.0
	(0.017)	(0.014)	(0.018)	(0.018)	(0.012)	(0.177)	(0.083)	(0.118)	(0.091)	(0.0
$Convexity$	−0.092***	−0.042***	−0.041**	−0.040**	−0.025***	0.023	0.243*	−0.069	−0.025	−0.0
	(0.011)	(0.012)	(0.017)	(0.020)	(0.006)	(0.211)	(0.127)	(0.122)	(0.084)	(0.0
$\sqrt{Days}$	0.199***	0.200***	0.135***	0.120***	0.104***	0.317	0.134	−0.070	0.349***	0.122
	(0.009)	(0.011)	(0.012)	(0.015)	(0.007)	(0.469)	(0.262)	(0.440)	(0.107)	(0.0
$Volatility$	0.261***	0.148*	0.157	0.204**	0.204***	1.389	−0.776	−0.274	1.463***	0.18
	(0.070)	(0.077)	(0.118)	(0.097)	(0.039)	(1.302)	(0.779)	(0.646)	(0.461)	(0.0
$Convexity$ × *Rank: First*	0.086***	0.048***	0.047***	0.070***	0.030***	−0.016	0.051	0.114	−0.077	0.04
	(0.014)	(0.014)	(0.018)	(0.023)	(0.010)	(0.169)	(0.112)	(0.165)	(0.121)	(0.0
$Convexity$ × *Rank: Second*				0.004	0.022**				−0.247***	0.0
				(0.023)	(0.010)				(0.070)	(0.0
$Convexity$ × *Rank: Second Last*			−0.043**	−0.017	−0.016*			−0.076	−0.223*	−0.0
			(0.020)	(0.020)	(0.009)			(0.131)	(0.121)	(0.0
$Convexity$ × *Rank: Last*		−0.049***	−0.030	−0.080***	−0.046***		−0.192	0.046	−0.173	−0.06
		(0.015)	(0.022)	(0.023)	(0.009)		(0.131)	(0.106)	(0.131)	(0.0
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Return Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	35,136	29,082	22,536	17,077	66,533	2,806	2,363	1,857	1,398	8,6
Adjusted R^2	0.210	0.219	0.229	0.277	0.276	0.129	0.466	0.379	0.546	0.4

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table A.9: Variation in the influence of *Convexity* on selling propensity with ranks and trader age

Number of Stocks in the portfolio	*Age* < 50					*Age* ≥ 50				
	Two	*Three*	*Four*	*Five*	≥ *Six*	*Two*	*Three*	*Four*	*Five*	≥ *S*
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(
$Portfolio^+$	−0.279***	−0.112***	−0.084***	−0.086**	−0.042***	−0.238***	−0.084***	−0.076***	−0.044	−0.045
	(0.016)	(0.018)	(0.022)	(0.039)	(0.011)	(0.018)	(0.020)	(0.024)	(0.027)	(0.0
$Stock^+$	0.250***	0.084***	0.113***	0.080***	0.044**	0.189***	0.101***	0.090***	0.075***	0.0
	(0.023)	(0.022)	(0.025)	(0.030)	(0.019)	(0.026)	(0.022)	(0.025)	(0.024)	(0.0
$Convexity$	−0.089***	−0.046***	−0.049*	−0.074*	−0.029***	−0.094***	−0.049**	−0.076***	−0.038	−0.029
	(0.017)	(0.016)	(0.028)	(0.041)	(0.010)	(0.019)	(0.022)	(0.026)	(0.027)	(0.00
$\sqrt{Days}$	0.199***	0.225***	0.131***	0.151***	0.094***	0.230***	0.226***	0.164***	0.161***	0.121
	(0.016)	(0.018)	(0.024)	(0.035)	(0.010)	(0.014)	(0.020)	(0.026)	(0.024)	(0.0
$Volatility$	0.236*	0.136	0.326**	0.143	0.218***	0.316***	0.138	0.132	0.315*	0.202
	(0.123)	(0.103)	(0.141)	(0.099)	(0.055)	(0.106)	(0.130)	(0.155)	(0.180)	(0.04
$Convexity$ × *Rank: First*	0.093***	0.080***	0.046	0.060	0.036**	0.066***	0.053**	0.073**	0.072**	0.02
	(0.020)	(0.020)	(0.030)	(0.045)	(0.015)	(0.021)	(0.025)	(0.030)	(0.036)	(0.0
$Convexity$ × *Rank: Second*				−0.019	0.032**				−0.017	0.0
				(0.044)	(0.015)				(0.030)	(0.0
$Convexity$ × *Rank: Second Last*			−0.012	−0.004	−0.028**			−0.052	−0.012	−0.0
			(0.029)	(0.047)	(0.013)			(0.031)	(0.030)	(0.0
$Convexity$ × *Rank: Last*		−0.083***	0.010	−0.061	−0.052***		−0.044*	−0.015	−0.083***	−0.053
		(0.018)	(0.033)	(0.047)	(0.014)		(0.025)	(0.035)	(0.032)	(0.0
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Return Rank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Trading day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	19,827	15,690	11,575	8,205	32,332	18,115	15,755	12,818	10,270	42,8
Adjusted R^2	0.234	0.274	0.302	0.340	0.302	0.239	0.278	0.280	0.372	0.3

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2. scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month l and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statis significance at 1%, 5%, and 10% levels, respectively.

Table A.10: Variation in the influence of Convexity on selling propensity with ranks: Extended sample analysis

	Dependent variable: $Sell\ Indicator_{ijt}$				
Number of Stocks in the portfolio	Two	$Three$	$Four$	$Five$	$\geq Six$
	(2)	(3)	(4)	(5)	(6)
$Portfolio^{+}$	−0.023***	−0.013***	−0.009***	−0.008***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Stock^{+}$	0.017***	0.010***	0.007***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Convexity$	−0.003***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0002)	(0.0003)	(0.0004)	(0.001)	(0.0004)
$\sqrt{Days}$	0.007***	0.007***	0.007***	0.006***	0.004***
	(0.0002)	(0.0003)	(0.0004)	(0.001)	(0.0004)
$Volatility$	0.031***	0.026***	0.024***	0.031***	0.024***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)
$Convexity$ × *Rank: First*	0.004***	0.004***	0.003***	0.005***	0.005***
	(0.0003)	(0.0004)	(0.0005)	(0.001)	(0.001)
$Convexity$ × *Rank: Second*				0.001	0.003***
				(0.001)	(0.0005)
$Convexity$ × *Rank: Second Last*			−0.001***	−0.001*	−0.001***
			(0.0004)	(0.001)	(0.0004)
$Convexity$ × *Rank: Last*		−0.002***	−0.002***	−0.002***	−0.003***
		(0.0003)	(0.0005)	(0.001)	(0.0005)
Trader FE	Yes	Yes	Yes	Yes	Yes
Rank FE	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes
Trading day FE	Yes	Yes	Yes	Yes	Yes
Observations	3,729,489	2,020,564	1,229,058	754,218	2,073,159
Adjusted R^2	0.093	0.114	0.130	0.163	0.083

The dependent variable is an indicator variable that takes a value of 1 if investor i sells stock j on day t. The key explanatory variables are defined in Table 1 and Table 2 The scripts denoting each specific investor i, stock j, and trading day t have been omitted for the sake of brevity. In all regressions, we add investor level, stock × year-month level, and date level fixed effects. Robust standard errors clustered at the investor, stock, and date level are computed and reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.