FOMO Economics: External Reference-Dependence and Risk-Taking in Household Portfolios

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Abstract

Individual investors are sensitive to peer performance and particularly dislike "falling behind." We use unique granular data on transactions and holdings of retail investors to study portfolio adjustment in response to relative performance of their portfolios. We show that investor behavior is consistent with preferences over future wealth that are S-shaped around an external reference point provided by a salient market benchmark: if their portfolio lags the index they tend to increase the risky share of their portfolio, as well as purchase riskier securities, as characterized by high market beta, idiosyncratic volatility, and positive skewness. As the salience of the market index increases, investors become more sensitive to relative performance. The effect is asymmetric, more pronounced in bull market periods when investors might be most fearful of missing out on gains experienced by their peers, and does not fully reverse when individual portfolios are ahead of the market. Our evidence provides a novel perspective on the individual investors' demand for risky assets.

JEL Code: D14, G11, G12, G40, G41, G50, G51

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I Introduction

One of the central and enduring insights of behavioral economics is that people make decisions and evaluate potential losses and gains relative to a reference point rather than in absolute terms. According to prospect theory, a reference point represents the baseline from which individuals assess possible outcomes, as changes relative to this point carry perceived value beyond absolute wealth levels (Kahneman and Tversky, 1979). Reference points can vary by context and individual circumstances, influenced by factors such as personal experiences, expectations, and social norms, yet a unified and generally accepted theory of reference points remains elusive (Kőszegi and Rabin, 2006). Relative wealth concerns are a potentially important source of reference dependence, whereby the desire to "keep up with the Joneses" drives individual risk attitudes (Abel, 1990; Haisley, Mostafa, and Loewenstein, 2008; Roussanov, 2010).

In this paper, we establish that investors' risk-taking and trading behavior depend on their portfolio performance relative to a natural external reference point: the market index that represents the relevant peer group of investors. Using a granular data set on portfolios of retail investors in Israel, we show that investors actively adjust their trading behavior and risk exposure based on their portfolio performance relative to the salient benchmark index. Investors whose portfolios underperform the benchmark trade more frequently and in larger volumes. Specifically, they have a nearly 18% higher propensity to trade, with 4.6% higher volumes of the buy transactions net of sell transactions, if the portfolio underperforms the index. Notably, these investors shift toward riskier assets, increasing their exposure to stocks, equity mutual funds, and ETFs, while reducing allocations to safer assets, such as bonds. Investors that have underperfomed over the most recent three months conduct 2.7% higher net trading in risky securities and 1.6% larger trades in high-beta stocks of the sample means, indicating a desire to increase risk, presumably in order to "catch up" with the market. Moreover, the portfolio-wide beta and overall share of risky holdings rise, with the largest adjustments occurring among investors with initially low risk exposure. This risk-taking behavior is asymmetric: while underperforming investors actively increase risk, outperforming investors do not proportionally de-risk, reinforcing a convex risk-adjustment pattern consistent with prospect theory and loss aversion. These effects are stronger in rising markets, suggesting that the "fear of missing out" on market gains drives stronger trading and risk-taking responses during "bull" markets. These patterns are consistent with an S-shaped value function postulated by prospect theory, with the kinked inflection point centered at the "peer group" portfolio return, whereby lagging the peers causes risk-seeking behavior, where as being ahead results in the desire to preserve the relative position.

The interpretation based on an S-shaped objective around the external reference point would imply that, having "caught up" with the market, investors invest more conservatively, aiming to preserve their relative position. We consider a subsample of investors that had previously underperformed but have been able to get ahead (e.g., outperforming the market over a six-month period while having underperformed in the first three months of that period). We find that these investors reduce the riskiness in their portfolios, including both their market beta and volatility, and increase portfolio diversification by holding a greater number of securities, although with smaller magnitudes. At the same time, these investors tend to maintain the beta of their portfolio with respect to the market benchmark that is (somewhat) greater than one, which would help preserve there relative performance vis-a-vis the market index, consistent with them exhibiting an aversion to relative underperformance.

In order to test whether the effect of performance relative to the market index on trading behavior is related to social interactions we examine investor trading behavior around holiday gatherings. If investors seek to avoid performing worse than others (as proxied by the market index), this tendency is likely to intensify ahead of anticipated intensive social interactions with the relevant peers, such as holiday gatherings with family or friends. Once peer performance has been revealed and there is more time until the next meeting, the incentive to "keep up with the Joneses" is temporarily weakened. Consistent with this intuition, we find that investors whose portfolios lag the market trade more actively prior to a central Jewish holiday, particularly in riskier stocks, than immediately after the holiday.

In addition, we examine the role of market index salience and visibility in shaping investor behavior. In order for the market index to serve as a reference point, it should presumably be representative of the wealth of one's peers, as well as be easily observable. In Israel, the leading stock indexes of the Tel-Aviv Stock Exchange (TA35 and TA125) are widely covered by financial media and displayed on trading platforms, making it easy for investors to compare their portfolio performance to the market indexes. A key test of salience comes from a 2017 market index reform, which increased the number of stocks in these indexes and changed their weighting structure. The results show that around the time of the reform, investors with underperforming portfolios increased their trading activity, particularly in riskier, high-beta securities and newly added stocks. This suggests that heightened index visibility led to greater investor attention and trading responses as the market index became more representative of peer wealth.

Further analysis examines whether investors treat other market indexes as reference points, depending on their visibility on the trading platforms available to them. While the Nasdaq 100, which is prominently displayed, affects the trading behavior of investors with higher foreign asset exposure, other global indexes such as MSCI World and S&P 500—despite being theoretically more diversified benchmarks—do not significantly influence investor decisions. Similarly, European indexes (DAX, FTSE), which are not displayed on the trading platform, have no measurable effect on investor behavior, even among those who trade European assets. These findings underscore that investors primarily adopt reference points that are both highly salient and perceived as relevant representations of "peer" wealth, rather than those that might be optimal from a modern portfolio theory perspective, or the most diversified ones.

Finally, we examine a range of alternative explanations for the observed trading behavior. In particular, we demonstrate that changes in investors' risk aversion, overconfidence, alternative reference points, investor learning and trading ability, social learning, portfolio rebalancing, the disposition effect, security salience, or momentum investing cannot fully account for the effects that we document.

This paper builds on and contributes to several different strands of the literature. There is a growing literature showing that individual risk-taking is consistent with S-shaped preferences around a "social" reference point. Dijk, Holmen, and Kirchler (2014); Frydman (2015); Genakos and Pagliero (2012) uses neural imaging data from an experimental asset market and shows that a peer's portfolio allocation has a causal effect on a subject's portfolio choice because a higher return by the peer is perceived as particularly unpleasant, consistent with a "kink" point suggesting a desire to "keep up with the Joneses." Experimental studies show that informing investors that they are lagging behind their peers increases their risk taking (Kirchler, Lindner, and Weitzel (2018), Kirchler and Kirchler (2024), Schwerter (2024)). Ager, Bursztyn, Leucht, and Voth (2022) document such behavior among German WWII fighter pilots. We document novel evidence of similar behavior in a representative sample of retail investors.

Our evidence points to the importance of "local" peer wealth as the relevant reference point. Luttmer (2005) and **?** emphasize the role of local peer comparisons in driving real income concerns. DeMarzo, Kaniel, and Kremer (2004) develop a model in which individuals competing for local resources herd into risky portfolios that are biased towards local assets rather than diversifying more broadly, consistent with our evidence of investors reacting to their "local" market index rather than the "global" ones.[1]

[1] There is a large literature on the role of social interactions in driving retail stock trading, e.g. Kaustia and Knüpfer (2012), Heimer and Simon (2015), Heimer (2016), and Gelman, Hirshleifer, Levi, and Reiter-Gavish (2024). Hong, Jiang, Wang, and Zhao (2014) show that retail investors to excessively trade small local stocks, especially when their peers are wealthier on average (holding own wealth constant), consistent with the idea of status concerns and "keeping up the with the Joneses."

Our findings also contribute to the literature on the role of reference points in a variety of settings, including negotiations, mergers and acquisitions, real estate transactions, etc. (Babcock, Wang, and Loewenstein, 1996; Baker, Pan, and Wurgler, 2012; Genesove and Mayer, 2001; Hart and Moore, 2008). Other papers show that reference point valuations are likely be successful in explaining price movements, (e.g., Gómez, Priestley, and Zapatero (2016, 2009); Peng and Xiong (2006)). We show that retail investors use the relevant market index as a salient reference point, potentially impacting prices of the securities they trade.

Much of the literature on the effects of prospect theory and reference point on portfolio decisions has focused on which securities investors sell and when (e.g., the disposition effect), and their consequences for stock prices (e.g., Shefrin and Statman (1985); Odean (1998); Ben-David and Hirshleifer (2012)).[2] analyze the effect of forecast bias affects individual investors' stock trading. Our analysis extends this literature by showing the impact of an external reference point on buy and sell transactions, as well as their net effect. In that way, we contribute to the developing literature on the buy and sell decisions of retail investors (e.g., Andersen, Dimmock, Nielsen, and Peijnenburg (2025)).

Our evidence provides a new perspective on the widely documented demand for "risky" assets by retail investors. Barberis and Huang (2008) show a positively skewed security can be "overpriced" and can earn a negative average excess return. Barberis and Xiong (2012) present a model of realization utility that sheds light on a number of puzzling facts, including the disposition effect, the poor trading performance of individual investors, the higher volume of trade in rising markets, the effect of historical highs on the propensity to sell, the individual investor preference for volatile stocks, the low average return of

[2]While most of the literature on the disposition effect focuses on retail investors, Frazzini (2006) shows that professional mutual fund managers display similar behavior, potentially distorting asset prices. Interestingly, Akepanidtaworn, Mascio, Imas, and Schmidt (2023) show that asset managers' *buying* decisions do not appear to be subject to behavioral biases while selling decisions are. Han, Roussanov, and Ruan (2021) show that mutual funds underperforming their peers or the benchmark increase their risk taking, which can be interpreted as rational risk shifting that arises from the convex response of investor flows to performance.

volatile stocks, and the heavy trading associated with highly valued assets. Bali, Cakici, and Whitelaw (2011) find a negative and significant relation between the maximum daily return over the past one month and expected stock returns. Boyer, Mitton, and Vorkink (2010) find that expected idiosyncratic skewness and returns are negatively correlated, and that expected skewness helps explain the phenomenon that stocks with high idiosyncratic volatility have low expected returns. Mitton and Vorkink (2007) present a model of investor asset holdings where investors have heterogeneous preference for skewness, which can explain investor underdiversification. Most closely related to our work, Aristidou, Giga, Lee, and Zapatero (2022) show that such aspirational utility generates preference for skewness. When their portfolios underperform the market, investors adjust their portfolios towards positively-skewed assets in order to "catch up" and not "fall behind," consistent with the market return acting as an "aspiration" level. Similarly, Bali, Gunaydin, Jansson, and Karabulut (2023) provide evidence consistent with the hypothesis that social status concerns explain wealthy investors' demand for high-risk stocks, leading to overpricing and low future returns for such stocks.

II Data and Institutional Background

II.A Data Description

To study investor's response when her portfolio lags the market, we utilize proprietary data on the transactions and holdings of retail investors from one of the leading financial institutions in Israel. The data includes the non-retirement portfolios[3] and the trading activity between 2014-2022 for a sample of 78,796 accounts. For each transaction the data includes the date, whether it is buy or sell, security identification number, total value,

[3]The financial institution offers a variety of financial services to households and firms. Individuals have a single account from which they conduct various transactions. We only observe their trading activity and holdings of financial assets, and do not have access to their cash holdings or other transactions within the account.

number of securities (which allows us to calculate the security's transaction price), how the order was executed (i.e., via the Internet, the bank's branch, or a bank's securities trader), and whether it was advised by the bank's financial adviser.

For every account, we observe the number of holders, establishment date, month-end total value of domestic and foreign securities held, monthly (net) salary, and a proxy for financial wealth (includes value of the whole investment portfolio, total deposits and foreign currency balance). About 36% of the accounts have one holder, 58% with two holders, and the rest with more than two holders (see Table I). In the paper, we use interchangeably accounts and investors, as we cannot identify who of the account holders performs the trades.

At the individual level, the data includes gender, age, occupation, marital status, indication of having children, address, and indication of home ownership.

Market price data for assets traded on the Tel-Aviv Stock Exchange was obtained from the exchange's website; for foreign assets we use CRSP and Datastream.

As expected, the investors in our sample are slightly older and have higher salaries compared to the Israeli population. These are the individuals who have the resources and the knowledge to trade on the stock market, thus more likely to set up a trading account. Table I shows that on average, two trades are conducted per month, with high dispersion between accounts. The median account performs less than one trade per month. Comparing the holdings of investors in our sample with data for US households (based on the average from the SCF for the years 2016-2022), the portfolios of both groups have similar compositions.

II.B The Israeli Stock Market

The Israeli stock market, led by the Tel Aviv Stock Exchange (TASE), is the platform for trading of financial securities in Israel. It is a fully computerized exchange that aligns with the standards of leading global stock markets. In the last decade, trading volumes have doubled, indicating robust trading and engagement by the different market players. Additionally, the market cap of TASE-listed firms has significantly grown. By December 2022, there were 548 listed companies, with a market cap of $270 billion, equity daily volume of $683 million, and a bond market turnover of $1 billion.

Trading on the Israeli stock market is prominently marked by its key indices: the TA35 Index, spotlighting the 35 companies with the greatest market capitalization. The TA35's composition reflects the country's economic landscape featuring a robust representation of high-tech, banking, and healthcare sectors, indicating these sectors' significant contribution to the local economy. Beyond the TA35 index, the TA125 index includes a wider range of the 125 companies with the largest market capitalization on the Israeli stock exchange. This index extends further into real estate, energy, and consumer goods.

As of 2022, the direct equity ownership by retail investors accounted for 18% (compared to 22% in the U.S.). Israeli institutional investors, such as pension funds and insurance companies, play a significant role in the stock market, accounting for around 60% of equity ownership in 2022.

Foreign investors, including institutional investors, also play a key role in trading on TASE. The extent of foreign institutional investment is particularly notable in leading companies and sectors that have a global presence or are part of international indices, as Israel is classified as a developed market in the MSCI World Index. In 2022, net purchases of equities traded on TASE by foreign residents amounted to US$3.9 billion, following purchases in similar amounts in 2021, according to the Bank of Israel.

Around 30% of the companies composing the TA35 are traded in another stock market (dual-listed companies). In addition to their presence on TASE, it is common for Israeli companies, especially those in high-tech, pharmaceuticals, and biotech sectors, to seek listings on global exchanges such as NASDAQ, NYSE, and London Stock exchange. This allows them to access a broader investor base and more significant capital markets.

II.C Variable Definitions

In this paper, we examine the relative performance of an investor's portfolio compared to the market. The literature has not identified a specific time horizon as most relevant for retail investors when evaluating performance. The evaluation window must be sufficiently long for investors to notice performance differences, particularly since many do not monitor the market daily, and to potentially trigger trading activity. However, if the window is too long, past performance may lose relevance. Accordingly, we adopt a three-month evaluation period for all variables. We also conduct robustness tests using alternative time windows—year-to-date and the preceding 12 months—and find that our results remain consistent.

The main Israeli stock indexes (TA35 and TA125) receive extensive coverage in the Israeli media, similar to the coverage of *Dow Jones Industrial Average*, S&P500, and Nasdaq100 in the U.S.. Hence, these indicies are salient behcmarks for most inestors. As a result, these indexes serve as salient benchmarks for most investors. Moreover, the trading platform of the financial institution in our data provides all investors with information on both their portfolio returns and the returns of the TA35, TA125, and Nasdaq 100, irrespective of their portfolio composition. This feature makes comparisons between individual portfolio performance and market benchmarks particularly straightforward.

Our main proxy for the market benchmark index is the TA35 index. As a robustness, we verify that the results remain consistent when using the TA125 index. Our focus in this paper is on the effect of relative underperformance, which is estimated in two ways. First, we use a dummy that equal to one if the portfolio three-month return lags the corresponding TA35 return, and zero otherwise[4]. As an alternative measure, we construct a continuous variable calculated as the difference between the TA35 and the portfolio returns over a given period, such as the last three months.

[4]We have access to the financial assets held and traded by investors, we do not observe cash holdings (as explained in Section II.A).

We estimate security riskiness using a dummy variable that equals unity if the security is a stock, equity mutual fund, or equity ETF, and zero if the security is a bond or a bond fund. For risky securities, we measure the riskiness of the asset with an indicator whether its beta is in the top tercile. The security's beta is calculated using daily data over three months ending at month *t-1* using the TA35 index as the market portfolio and the three-month Israeli government bond yield as the risk-free rate. We also calculate the security's volatility using daily data over three months ending at month *t-1*.

The main dependent variable in the account-level specifications is an indicator equal to one if the investor executes any trade in a given month, and zero otherwise. Another outcome variable includes the trade size in the account scaled by the investor's lagged total value of assets in the brokerage account. The trade size is calculated as the value of the buy transactions net of sell transactions. Other dependent variables include the share of risky holdings (stocks, equity mutual funds and ETFs) in the portfolio, the overall beta and volatility of the portfolio, calculated as the weighted average of the risky assets holdings. The main outcome variable in the security-level specifications is the trade size of a given security, scaled by the investor's lagged total value of assets in the brokerage account. In addition, we employ a dummy variable equal to one for buy transactions and zero for sell transactions.

In all our specifications, we control for portfolio-level time-varying changes, namely the three-month return and the three-month volatility. At the security level, we additionally control for whether the security has a high beta. Further, we control for whether the security's return is below the portfolio return, and when using the continuous measure of portfolio underperformance, we instead control for the return difference between the security and the portfolio as well as the security's three-month return.

III How Do Investors Respond When their Portfolio Lags the Market?

In this section, we analyze investors' responses to their portfolio performance relative to the market. Specifically, we examine their propensity to trade and the size of their trades (Section III.A), as well as the effect of relative underperformance on risk-taking (Section III.B).

III.A The Effect on Trading Propensity

We start the analysis by examining the likelihood that retail investors trade when their portfolios underperform the market. To do so, we estimate the following account-level specification:

$$\mathrm{Y}_{it} = \beta_1 \text{Portfolio lags market}_{it} + \beta_2 \text{Controls}_{it} + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{1}$$

Where Y stands for different outcome variables. First, we use *Trade*, an indicator variable if investor i executes any trade in month t. Next, we study the effect on the trade volumes of the buy transactions net of sell transactions of account i in year-month t, scaled by the investor's lagged total value of assets in the brokerage account. *Portfolio lags market*, a dummy variable equal to one if the portfolio return is below the corresponding TA35 return, and zero otherwise. We control for portfolio-level time-varying changes, namely the cumulative investor's return and portfolio volatility. α_i is the account-fixed effect, which controls for time-invariant account-specific characteristics (such as financial literacy, risk aversion and preferences), α_t is the year-month fixed effect that controls for the macro and market factors that influence all individuals in a given year-month. Standard errors are clustered by account.

Table II presents the results for this specification. In columns 1 and 2, the dependent variable is an indicator for whether the investor executes any trade in the account. Column 1 includes only our main explanatory variable, while column 2 adds the control variables. The coefficients are positive and statistically significant in both columns, with economically meaningful magnitudes: investors with underperforming portfolios are 17.9% more likely to trade relative to the sample mean (column 2). Columns 3 and 4 examine trade size, focusing on months in which the investor executes any trade. We find that underperforming portfolios are associated with 4.6% higher trade volumes relative to the sample mean (column 4).

These results provide initial evidence that investors respond to changes in the relative performance of their portfolios. Specifically, they use the salient market portfolio as a reference point when evaluating performance, beyond other influencing factors. Investors whose portfolios lag the market are more likely to trade and do so with larger volumes compared to those who outperform. In the next section, we examine how investors adjust their portfolios to avoid "falling behind," focusing on their risk-taking and trading decisions in response to market movements.

III.B The Effect on Investor Risk-Taking

In this section, we demonstrate that the relative underperformance of an investor's portfolio influences their risk-taking. To this end, we exploit the granularity of our dataset and estimate the following security-level baseline specification:

$$\begin{aligned}\text{Trade Size}_{ist} =& \beta_1 \text{Relative Underperformance}_{it} \times \text{High beta security}_{st} + \beta_2 \text{Controls}_{st} \\ &+ \beta_3 \text{Controls}_{it} + \alpha_i + \alpha_s + \alpha_t + \varepsilon_{ist}. \qquad (2)\end{aligned}$$

Here, *Trade Size* represents the trade volumes of the buy transactions net of sell transactions in security s in account i on date t, scaled by the investor's lagged total value of assets in the brokerage account. We measure portfolio underperformance relative to the market in two ways. First, we use *Portfolio lags market* from Equation 1. As an alternative, we use a continuous variable, *Market return–Portfolio return*, calculated as the difference between the TA35 and the portfolio returns. This variable is interacted with *Risky security*, a dummy equal to one if the security is a stock, equity mutual fund, or equity ETF, and zero if it is a bond or bond fund. For risky securities, we further measure riskiness with *High beta security*, an indicator equal to one if the security's beta (as defined in Section II.C) is in the top tercile. Portfolio-level time-varying characteristics, as in Equation 1, are included. We also control for the following security-level time-varying variables: an indicator for whether the security return is below the portfolio return, and, when using the alternative measure of underperformance, the difference between the security and portfolio returns as well as the security's three-month return. α_i denotes the account fixed effect, α_s the security fixed effect, capturing time-invariant asset-specific characteristics (such as prominence, firm characteristics, industry, and media coverage), and α_t the date fixed effect, controlling for macro and market factors affecting all individuals on a given date.[5] Standard errors are clustered by account.

Table III presents the results of this specification. in both Panels, columns 1 and 3 include account, security and time fixed effects, columns 2 and 4 include security and account-time fixed effects, which allow us to capture any time variant account-specific changes, such as changes in risk-aversion, income, etc. In Panel A, we test the trading in risky securities (as defined above). Analyzing the interaction terms, we find them positive and statistically significant across all columns, indicating that investors increase risk in response to under-performing portfolios. Investors whose portfolios lag the market conduct 2.7% higher trading volume of the sample mean in risky securities (column 2). A one percentage point increase in the difference between the market and the portfolio returns is associated with a 0.4% higher trading volume of the sample mean in these

[5] All results in this specification and subsequent empirical tests are robust to using year-month fixed effects instead of date fixed effects.

securities (column 4).

In Panel B of Table III, we focus on the universe of risky securities, analyzing trading in high-beta stocks. We find that investors with portfolios lagging the market conduct 1.6% higher trading volume of the sample mean in high-beta securities (column 2). A rise of one percentage point in the difference between the market and the portfolio returns is associated with 0.3% higher trading volume of the sample mean in high-beta securities (column 4).

Naturally, if we were to focus only on buy transactions, the magnitudes would be larger. However, our goal in this paper is to show the net effect; therefore, in the remaining specifications, we analyze trade size as the net of buy and sell transactions. Much of the existing literature has focused on the effects of prospect theory and reference points on sales, such as the disposition effect, and its implications for the stock market (e.g., Frazzini (2006); Shefrin and Statman (1985)). Our analysis extends this literature by showing the impact of an external reference point on buy and sell transactions, as well as their net effect. We show that retail investors shift toward riskier assets when their portfolios underperform the market. This allows us to provide a more holistic understanding of the effect of relative underperformance and the fear of "falling behind."

In robustness tests, we verify that the results hold when using alternative return periods (YTD and 12 months instead of three months), a different market index (TA125 instead of TA35), and after excluding the COVID period, as wealth accumulation among affluent investors during this time may have influenced their trading behavior. We also show that the baseline results hold using other measures of security risk, namely its volatility (in Section III.C) and return skewness (Section VI).

Next, we analyze how an investor's ex-ante portfolio riskiness affects her response to underperforming the market and the impact on overall portfolio composition. To this end, we divide investor portfolios into three buckets based on the share of risky holdings (stocks, equity mutual funds, and ETFs): below 30%, 30%-60%, and above 60%. Table IV presents portfolio-level analyses based on Equation 1, with the outcome variable defined as the share of risky assets (columns 1-3) and the portfolio's overall beta (columns 4-6). Across the three risk buckets, the results show that both the share of risky assets and the portfolio beta increase, with the largest increases observed among investors with the least prior exposure to risk.

These results indicate that all investors increase the riskiness of their portfolios when they lag the market. However, these adjustments have substantial effects on overall portfolio composition, particularly for investors who were previously less exposed to risky securities, as the changes markedly increase their total risk exposure.

III.C Asymmetric Effects

The notions of "Fear of missing out" and "keeping up with the Joneses" suggest that the desire to match peer performance is particularly strong when said peers are doing well. This intuition is corroborated by the experimental evidence in Frydman (2015), who shows that subjects react particularly negatively if their portfolio lags the peers' when that latter does well (i.e. in an "up" market state), even if own portfolio return is positive. In order to test whether this pattern extends to the behavior of retail investors, we examine whether underperforming investors increase risk differently during periods of positive versus negative market returns. Estimating the security-level specification in Equation 2, we find in Panel A of Table V that investors with lagging portfolios tap more into riskier securities in both periods. However, the effect is more prominent when the market goes up. When investors' portfolios lag the market in bearish periods, the net size of stock purchase, in particular interacted with a high risk stock, is still positive, but lower than in the bull market periods. Investors are more reactive in rising markets, suggesting that the "fear of missing out" on market gains drives stronger trading and risk-taking responses during "bull" markets.

The fact that the results are not confined to specific market periods helps address alternative explanations—such as changes in risk aversion or related factors—as the primary drivers of the findings, rather than the market portfolio serving as a reference point (as discussed in moredetail in section V.A).

Our results remain robust when we replace the measure of security risk from systematic risk to total risk. Panel B of Table V, presents the results for the specification in Equation 2, using the security volatility as the measure of risk. Columns 1 and 4 show that the baseline findings continue to hold when volatility is used instead of beta. As in Panel A, we then separate the analysis into bull and bear market periods.

In Kahneman and Tversky (1979) the prospect theory value function exhibits a kink at the reference point. This implies asymmetric behavior of investors who are in domain of "gains" relative to the reference point as opposed to "losses": being "ahead" does might make one more cautious, but, if the reference point is stochastic, e.g. driven by peer wealth, the investor's objective is to not "fall behind," and hence aim for a portfolio beta close to unity with the reference portfolio, but not lower. In contrast, for investors who are lagging behind already the objective of "catching up" with the peers requires ramping up risk, in particular having a beta that is greater than one.

Thus, we study whether the investor's response is symmetric for underperforming vs. outperforming portfolios. We perform the security-level specification in Equation 2 using *Security return–Portfolio return* as the explanatory variable, and split between periods in which the market outperforms the portfolio and periods when the it underperforms the investor's portfolio. Panel A in Table VI presents the results of this specification. First, we include the whole sample (columns 1 and 2). Then, we distinguish between periods with positive market returns (columns 3 and 4) and periods with negative market returns (columns 5 and 6). We find that the effect for underperforming portfolios is more than twice as strong than for the outperforming portfolios. This indicates that the changes in the risk of investors' portfolios are S-shaped around the return of the market, potentially with a kink at the reference point, as hypothesized by (Kahneman and Tversky, 1979).

To further test this asymmetry, we perform a within-individual analysis, in which we study the behavior of a subsample of outperforming investors that previously were underperforming. The idea is to analyze how the same individual adjusts the portfolio after successfully achieving the goal of beating the market. If investors reduce risk less than they increased it when the portfolio underperformed the market (or even do not decrease risk at all), it indicates an asymmetric response.

To this end, we perform the account-level specification in equation 1 changing the main explanatory variable to *Portfolio outperforms market*, an indicator whether the portfolio return currently exceeds the market return, and in the past the portfolio underperformed the market. For the outcome variables, this time our focus is on different portfolio risk characteristics. Specifically, we explore the portfolio's overall beta, overall volatility[6], and the total number of securities in the portfolio.

Panel B in Table VI presents the results of this specification. Consistent with the results in Panel A, we find that investors that beat the market after underperforming it reduce the riskiness in their portfolios, both the beta and the volatility, and increase the number of the different securities held.[7] Examining the beta of their portfolios, we find that outperformance is associated with a higher probability of maintaining aggressive strategy (relative to underperformance). This suggests that while underperforming investors actively increase risk, outperforming investors do not proportionally de-risk, reinforcing a convex risk-adjustment pattern consistent with prospect theory and loss aversion. This analysis also provides additional support that investors indeed refer to the market as a reference point. The reason is that they conduct active trading in response to lagging the market, and then they revert slightly back once they reach the goal.

[6]For this outcome variable, we exclude portfolio volatility from the control variables.

[7]In Panel C of Table XI in Section V.C, we use the same outcome variables to conduct the portfolio-level analysis for the full sample of investors. Comparing the magnitudes, the effects for this subsample are smaller.

In Panel C, we rerun the specification from Panel B using a rolling five-month window. We redefine *Portfolio outperforms market* as an indicator equal to one if the portfolio underperformed the market over the first three months of the window but outperformed it over the subsequent two months. We restrict the sample to investors whose portfolios exhibit higher cumulative returns than the market, measured from the window's starting point. Similarly, in Panel D, *Portfolio outperforms market* is a dummy whether the portfolio underperformed the market over the first two months of the window but outperformed it over the subsequent three months.

The specific requirements (cumulatively outperforming right after underperforming) and the limited time-window analysis make both of these specifications nosier than the one in Panel B. However, the results remain consistent. These analyses allow us to show more clearly the asymmetric response of retail investors to the market portfolio, and specifically the S-shaped value function around the market index return.

III.D Trading Frequency

In this section, we provide additional evidence that investors' awareness of their relative portfolio performance increases their tendency to exhibit the type of "catching up with the Joneses" behavior vis-a-vis the market that we have documented. Investors can observe their relative performance only when they log into their accounts on the trading platform and view their portfolio returns. Because we do not observe login behavior, we proxy for attention using investors' trading frequency over the past three months.

Table VII presents the results of our baseline analysis in Equation 2, where we split the sample based on whether an investor's trading activity over the past three months is above or below the median.

Consistent with the results in previous sections, we find that investors who trade more frequently and whose portfolios underperform the market index increase the risk of their portfolios in an attempt to catch up. Comparing the magnitudes in Columns 1 and 2, the effect is more than 50% stronger among frequent traders when their portfolios lag the market, and approximately twice as large per one percentage point of underperformance. These findings support our central argument: investors exhibit an aversion to falling behind the market, and greater awareness of relative underperformance amplifies their behavioral response.

III.E Holiday Gatherings

Now we turn to provide more direct evidence that the market index serves as a peer group for investors. An investor seeks to avoid performing worse than others. This tendency is likely to intensify ahead of anticipated intensive social interactions with the relevant peers, such as holiday gatherings with family or friends. However, prior to the meeting, investors are less certain about whether they are underperforming their peers, making them more likely to use the market index as a proxy for peer performance before the holiday than afterward.

Having this intuition in mind, we perform an analysis around Passover, a central Jewish holiday traditionally celebrated with family gatherings. To show the effect of the holiday, we narrow the analysis for 1-month window around it. Since Jewish holidays follow the Lunar calendar, the dates on which the holiday falls vary substantially from year to year. Consequently, investor behavior around Passover is unlikely to be driven by seasonality, which is an additional empirical advantage.

We follow our baseline analysis in Equation 2 limiting the analysis only around Passover every year. We add the interactions of the main explanatory variables with *After*, a dummy equal to one for the month following the holiday, and zero for the preceding month. The rest of the variables are the same as in Table II. Table VIII presents the results of this specification. In columns 1 and 2 we include the indicator whether the investor lags the market, in columns 3 and 4 we utilize the continuous variable. The coefficients are negative, indicating that investors with portfolios lagging the market trade more *before* the holiday, particularly in riskier stocks. However, after the holiday, the market index is less informative as an indicator of peer effects, because investors are more likely to have already engaged in personal interactions, learned about their peers' performance, and have more time before the next meeting.

IV Salience of the Market Index

In previous sections we showed that the market serves as a reference point for investors. Consequently, they increase the riskiness of their portfolios when they underperform it. This holds beyond different portfolio and security characteristics.

For the market to serve as a reference point, it has to be accessible and easily observable. As mentioned in Section II.C, the main Israeli stock indexes (TA35 and TA125) are reported and covered by the general and the financial media. Additionally, the trading platform of the financial institution from which we received the data presents to all the investors the returns of their portfolios, as well as of the TA35, TA125 and Nasdaq100, regardless of the composition of their portfolios. This makes the comparison between the performance of the investor and the market straightforward. To provide a more direct evidence for the effect of market saliency on the investor's portfolio choices, we utilize a unique reform in the leading market indexes (Section IV.A). Then, we compare between indexes presented on the trading platform vs. those that do not, and analyze how this affects the investor's response (Section IV.B).

IV.A Market Index Reform

IV.A.1 Institutional Setting

In February 2017, TASE implemented a reform in the leading stock indexes. The main changes led to a rise in the number of shares included in each index, and reduction in the weight ceiling of each share in the index. Specifically, the Tel-Aviv 25 index was expanded from 25 shares to 35 shares, and its name was changed accordingly to Tel-Aviv 35 index (TA35). The maximum weight per share in the index was reduced from 10% to 7%. The Tel-Aviv 100 index was expanded by 25 shares to 125 shares, and its name was updated to Tel-Aviv 125 index (TA125). The key goals of the reform were to enhance the trading volume on TASE, increase public holdings in the leading indexes, and raise the dispersion of shares by reducing the concentration in the indexes (as about 70% of the index's weight was derived from the ten biggest stocks).

The reform was publicly announced in January 2016, approved in August that year and the implementation was completed on 9-February 2017. Each step of the reform was publicized in advance and covered by the financial and the regular media. Thus, we do not refer to it as an exogenous shock. Rather, we refer to the reform as an event study, arguing that it led to increased saliency and greater investor attention towards the updated market indexes and the newly added stocks. As supporting evidence, we indeed find in our data elevated total trading volumes in February and March 2017.

IV.A.2 Changing Salience of the Market Index

What is the role of salience in determining the relevant reference point? We focus on a narrow time window around the end of the implementation of the TA index reform and perform the following security-level specification:

$$
\begin{aligned}
\text{Trade Size}_{ist} = & \beta_1 \text{Relative Underperformance}_{it} \times \text{After}_t + \beta_2 \text{Controls}_{st} \\
& + \beta_3 \text{Controls}_{it} + \alpha_i + \alpha_s + \alpha_t + \varepsilon_{ist}.
\end{aligned} \tag{3}
$$

Where *After* is a dummy equal to one for the month of the reform and the following one, i.e., February-March 2017, and zero for the preceding two months. The rest of the variables are the same as in Equation 2. Column 1 in Table IX presents the results of this specification. In column 2, we add the triple interaction of *Portfolio lags market*, the *After* indicator and the *High beta security* indicator.

We find that investors with portfolios lagging the market index trade more securities in general (column 1)—and specifically riskier ones—around the index reform. The magnitudes are meaningful, with investors with portfolios lagging the market conduct 1.2% higher net trading volume of the sample mean in high-beta securities (column 2). This effect is similar, although a bit smaller, compared to the results in the baseline specification in Panel B of Table III.

In column 3, we study the effect of the added stocks to the market indexes, by exploring the triple interaction of *Portfolio lags market* and *After* with *Stock added*, an indicator equal to one for the added stocks to the TA35 or TA125. Here, we find that investors with portfolios lagging the market tap into the newly added stocks, indicating that the reform indeed increased the saliency of the market index.

The results remain consistent in columns 4-6. These columns are similar to the columns 1-3, respectively, only changing the indicator whether the portfolio lags the market to the continuous *Market return–Portfolio return* variable. Here, the magnitudes are even slightly larger than in Panel B of Table III.

IV.B Index Visibility on the Trading Platform

Another index that is presented on the trading platform to all the investors is the Nasdaq100. To test whether this index also serves as a reference point, we perform the baseline specification in Equation 2, changing the market index from TA35 to Nasdaq100. Panel A in Table X presents the results. For the full sample of investors (columns 1 and 2), we do not find evidence that this index serves as a reference point. This indicates that investors that trade mostly domestic assets (due to home bias) refer to the local market index (TA35 or TA125) as the reference point. However, focusing on investors with above median share of foreign securities holdings, we find that they tap into riskier securities when their portfolios lag the Nasdaq100. Comparing the magnitudes to the results in columns 1 and 3 in Panel B of Table III, here the effects are still meaningful although about one-third smaller.

According to the standard portfolio theory, the investor should maximize her risk-adjusted return by holding a highly diversified portfolio. The index that represents the most diversified portfolio should be the appropriate reference to evaluate the portfolio's performance. Thus, we would expect to find the strongest effect for the MSCI World Index, as it proxies the general world-wide stock market. The the next best proxy is the S&P500, given its leading role in the global stock markets and the global exposure of the firms included in the index. Changing the market index from TA35 to the MSCI and then to the S&P500, we find no such effect in Panel B of Table X, even focusing only on investors with above median share of foreign securities holdings. In columns 1 and 2, we perform the specification for the S&P500 as the market index and find statistically and economically weak effect that probably stems more from the correlation with the Nasdaq100. In columns 3 and 4, when using the MSCI as the market index, we find no results.

Further, in Panel C, we further verify that other indexes do not serve as reference points. Changing the market index to DAX (columns 1 and 2) and FTSE (columns 3 and 4)—indexes that are not presented on the platform, even for investors that invest in foreign assets, and specifically European ones—we do not find a statically significant effect.

Finally, to further show the effect of index saliency, in Panel D of Table X, we calculate the portfolio betas against different market indices among all investors (column 1) and for a subsample with above median share of foreign securities holdings (column 2). Here we find that the local TA35 index is the most relevant for a typical investor, followed by the S&P500, which is the more relevant for the more internationally diversified ones. However, the effect that we document in Panel B of Table X is stronger for Nasdaq.

Overall, these findings underscore that investors primarily adopt reference points that are both highly salient and perceived as relevant representations of "peer" wealth, rather than those that might be optimal from a modern portfolio theory perspective, or the most diversified ones.

V Alternative Explanations

In the previous sections, we showed that when investors lag the market index, they tap into riskier securities. We provided empirical evidence—both in a panel analysis, around the market index reform and around Passover—that the market serves as a salient reference point of peer performance, thus investors adjust their holdings based on their relative underperformance. In this section, we turn to discuss alternative explanations to the results. First, in Section V.A, we confirm that changes in investor's risk aversion and overconfidence cannot fully explain the observed effects. In Section V.B, we show that the observed effect of the market holds beyond other reference points that were found in the literature. In Section V.C we provide evidence that investor's learning is not the main effect behind the results. Section V.D discusses the distinction between the market serving as a social reference point and social learning. In Section V.E, we show that the results are not driven solely by portfolio rebalancing trades or the disposition effect. Section V.F confirms that security salience or momentum investing do not fully explain the observed effects. Finally, Section V.G shows that investor's trading skill is not the main driver of the results.

V.A Risk Aversion

A main concern arising from the observed changes in the investor's risk-taking is that they stem from variation in the investor's risk-aversion and overconfidence, rather than external reference point. Specifically, excessive returns in the investor's portfolio or good market periods were found in previous studies to affect risk-taking (Brunnermeier and Parker, 2005; Puri and Robinson, 2007). We deal with this concern in multiple ways.

First, in all the specifications we include the return and the riskiness of both the investor's portfolio and the security. We also control whether the security lags the market, not only the portfolio. Finally, we include granular fixed effects to capture any time-variant security and investor characteristics. This enables us to interpret the results beyond changes in risk-aversion.

In addition, our main measure of relative underperformance—the indicator if the portfolio lags the market—by construction presents the results as a comparison to instances where the portfolio outperforms the market. If risk-aversion were indeed the main channel, we would expect to find the rise in riskiness for outperforming portfolios, not for underperforming ones, consistent with the heightened overconfidence. Related, our results also hold in bearish periods of the market, while overconfidence is less likely to be the driver of the rise in risk during bad market conditions.

We also address this concern more directly by adding to the baseline specification at the security level in Equation 2 an interaction between the portfolio's return with the *High beta security* indicator. The idea is to capture any variation in investor risk-taking that arises from the return of her portfolio. Controlling for this interaction, we can interpret the coefficient of our main interaction term such as the effect holds beyond changes in overconfidence. Column 1 in Panel A of Table XI presents the results. We find that our main interaction term (*Portfolio lags market* with *High beta security*) remains statistically significant with a similar magnitude as in the baseline specification. The newly added interaction term between *Portfolio return* and *High beta security* is also statistically significant with a larger magnitude, indicating that risk-aversion indeed plays an important role in driving investors' trading behavior, but it does not interfere with the "FOMO" effect that we document.

V.B Other Reference Points

Another alternative explanation for the results is the standard prospect theory, which states that investors can have various reference points depending on the context and the circumstances.

One of plausible reference point is whether the portfolio earns money, rather than the return of the market. If the investor is in the domain of losses, she is more likely to gamble. To address this concern, we continue with the specification in column 1 of Panel A in Table XI, but this time, each month we split between investors with positive and negative portfolio returns (Columns 2 and 3 respectively). We find that the coefficient of our main interaction term (*Portfolio lags market* with *High beta security*) remains similar to the overall analysis. In column 4, we provide further evidence that the market portfolio serves as a reference point by showing that our main interaction term remains robust also for portfolios with negative returns in periods when the market goes down. We consider these periods as the ones in which investors are more likely to be in the domain of losses, as referred from the standard prospect theory.

It may be also the case that the market return captures the effect of a different reference point due to correlation between the market return and the return of the security from other reference points. Specifically, we analyze the purchase price (Grinblatt and Han, 2005), the 52-week high or low prices (George and Hwang, 2004; Huddart, Lang, and Yetman, 2009) as alternative reference points. We verify that the effect of the market holds beyond these reference points by adding to the security-level baseline specification in equation 2 the returns of each of these three prices. Panel B in Table XI presents the results. In column 1, we add the cumulative return of the security (only for securities purchased during the sample period). In columns 2 and 3 we add the return of the security from its 52-week high and low prices, respectively. The coefficients of the main interaction term remain statistically significant with similar magnitudes in all the columns.

Further, Li and Yu (2012) show that nearness to the Dow Jones Industrial Average index 52-week high and historical Dow high affect future aggregate market returns. To show that the observed effect is not driven by these reference points, in columns 4 and 5 of Panel B in Table XI we add indicators if the TA35 is at its 52-week or historical high, respectively. Our results remain robust.

V.C Learning and Diversification

Alternatively, underpeforming portfolios may indicate to the investors that their holdings are not diversified enough. Thus, if the portfolio lags the market it can drive the investor to learn how to catch up with the market using more diversification or start to mimic the market index. In this case, the observed effect captures this learning rather than the investor comparing to peer performance.

We address this concern in Panel C of Table XI by showing that investors do not diversify their portfolios. Performing the account-level specification in Equation 1, we change the left-hand side variable to the number of securities held in the portfolio (column

1), the portfolio's HHI calculated based on the number of securities (column 2), and portfolio's HHI calculated based on the holding amounts (column 3). The results indicate that the portfolios become more concentrated—with less securities held and higher HHIs. This is the opposite from what is expected by the learning argument. In columns 4 and 5, we rerun this specification for the overall portfolio beta and portfolio volatility as the outcome variables, respectively. Consistent with the higher concentration, the riskiness of the portfolios goes up, not down, for investors lagging the market.

A related concern is that underperforming the market index might drive investors to learn to purchase stocks that help them perform better. However, our results hold in bear markets, when investors are less likely to purchase risky securities as part of a learning process from the market. If learning indeed drives investor behavior, they are expected to act cautiously and reduce risk in response to market turmoil. Yet, we also test this more directly. If learning is indeed the case, investors are expected to by performing the specification at the security level (Equation 2) changing the outcome variable to raw and abnormal returns of the security. Columns 1-3 in Panel A of Table XII present the results for the following one-month, one-year, and two-year raw returns, respectively. Columns 4-6 present the results for the abnormal returns for the same time-windows. We do not find evidence that investors buy stocks that perform better.

V.D Social Learning

Another concern regarding our results might be that the observed effect of the market index on investor behavior stems solely from a correlation of the market index with social learning. There is a large literature on social learning through social interactions between investors in driving retail stock trading (Gelman, Hirshleifer, Levi, and Reiter-Gavish, 2024; Heimer and Simon, 2015; Heimer, 2016; Hong, Jiang, Wang, and Zhao, 2014). Investors tend to discuss and purchase more volatile and well-performing stocks, driving the rise in the riskiness of their portfolios. Additionally, social interactions encompass different types of peer effect, both social learning and reference dependence. However, the findings in the previous sections indicate that the observed effect in this paper cannot be explained only by social interactions. First, as part of our empirical strategy, all the security-level regressions (Equation 2) control for the return and the riskiness of the security. Additionally, in Panel B of Table XI we show that the effect of the market index holds when controlling for the stock's 52-week high/low price. Further, we demonstrated in Section III.C that the results hold not only in bull market, when investors are more likely to share success, but also in bear markets. Therefore, although we cannot fully rule out the effect of social learning through interactions, these results indicate that the effect of the market is distinct.

V.E Portfolio Rebalancing and Disposition Effect

The observed rise in risk for underperforming investors might be driven by portfolio rebalancing trades intended to restore the initial asset allocation, rather than the market serving as a peer reference point. We show that this alternative explanation cannot fully explain our results as they hold when adding to the baseline specification at the security level in Equation 2 the beta of the stock (beyond the the high-beta indicator), as well as the shares of the risky and safe holdings (as defined in Section II.C). Controlling for these factors allows us to estimate the effect of the market index beyond portfolio changes that might stem from rebalancing trades. Columns 1 and 2 in Panel B in Table XII present the results for the main explanatory variable. Our results remain consistent indicating that rebalancing trades are not the main mechanism of the results.

Alternatively, the reduction in risk for outperforming investors might result from selling high-performing, higher-risk stocks, while retaining underperforming stocks. To deal with this concern, we add to the baseline specification at the security level in Equation 2 the aggreagte return of the stock since the investor purchased it for the first time (in Section V.B we include the purchasing price; here we use this price to calculate the return). Our results do not change in Column 3 of Panel B in Table XII.

V.F Security Salience and Momentum Investing

An alternative explanation for investor trading response is that they trade salient securities—for instance, stocks covered by the media, top or bottom performers—or follow momentum investing strategy. In either case, our observed results stem from the correlation with the market index, rather than the market representing relative performance of peers. However, this is not consistent with our results in the previous sections. The effect of the market index holds in different market periods and securities, and not limited to specific ones. Specifically, in Section III.C we showed that the results hold both in bull and bear market periods, Section V.A demonstrates that the effects remain consistent for winning and losing securities, and the analysis in Section III.C provides evidence that underperforming investors purchase more the same security that outperforming investors sell.

We also conduct a more direct analysis by accounting for any time-variant changes in the security, such as security salience. To this end, we perform the baseline specification at the security level in Equation 2 including more granular fixed effects—bank account and security x three-month period. Column 4 in Panel B of Table XII presents the results of this analysis. The effect of relative underperformance still holds, with similar magnitude to those in Panel B of Table III.

V.G Investor Trading skill

Another concern is that our findings are primary driven by investor trading skill whereby a group of investors consistently outperforming or lagging the market index. In this case, the results cannot be attributed to a general pattern, but rather to a subsample of investors that make specific trading choices related to their trading skills. However, it is less likely to be the case, as in all our specifications (both at the account and the security levels) we control for investor's overall portfolio return and include investor fixed effects. In that way, we capture investor characteristics and performance, including trading skills. Thus, our results hold for any investor. Additionally, the analysis presented in Section III.C shows that the S-shaped behavior around the market return holds for the *same investor* when outperforming the market index, while previously lagging it, further indicating the effect of the market index as a relative peer group beyond investor-specific characteristics.

VI Robustness Tests

In this section, we conduct different robustness tests. First, in all our analyses we include three-month returns, both for the portfolio and the market. Thus, the relative underperformance measures are also calculated based on the preceding three months. To show that the results also hold for alternative return periods, we perform the baseline specification in Equation 2 using year-to-date returns, and then a rolling window of the preceding 12 months. Panels A and B of Table XIII present the results of this specifications, respectively. We find that the effects remain similar.

Next, we show that the results remain consistent for a different common Israeli index for the market return. As explained in Section II.B, the two main market indexes in Israeli are the TA35 and TA125. As throught the paper we use TA35, in Panel C of Table XIII we perform the baseline specification in Equation 2 changing the market index from TA35 to TA125.

Further, wealth accumulation of the wealthy investors during the COVID period might affect their trading behavior differently from other investors and differently from other periods. To this end, in Panel D of Table XIII we exclude this period from the baseline specification in Equation 2, and show that the results remain robust.

Finally, in Panel E of Table XIII we show that our baseline results hold using security skewness as an alternative measure of security risk. Performing the specification in Equation 2, in Columns 1 and 2 we use *High skew security* as the measure of security risk, an indicator whether the security is in the top tercile of the 3-month return skewness. In columns 3 and 4, the measure of risk is *High return security*, a dummy if the security is in the top 3-month return tercile. Consistent with the previous results, We find positive and statistically significant coefficients.

VII Conclusion

In this paper, we provide evidence that retail investors exhibit external reference-dependent behavior, treating the market index as a salient benchmark for their portfolio performance. Specifically, when investors "falling behind" the market, they react by increasing trading activity, shifting toward riskier securities, and adjusting their overall portfolio risk. This response is asymmetric, reinforcing the idea that investor behavior aligns with prospect theory and loss aversion—with stronger risk adjustments occurring in the domain of perceived losses rather than gains. Moreover, market saliency and visibility play a central role in shaping these behaviors, as investors primarily react to indexes prominently displayed on trading platforms, instead of more appropriate but less visible benchmarks.

Our findings have important implications for behavioral finance, market dynamics, and financial advisory practices. The evidence suggests that investors are not merely responding to absolute portfolio performance but are actively benchmarking themselves against the market and their peers, leading to potential excessive risk-taking in bull markets due to fear of missing out. This behavior may contribute to greater volatility and mispricing in financial markets, particularly in assets with lottery-like payoffs, such as high-beta and high-skewness stocks. Future research could explore how investment platforms, financial advisors, and media narratives shape investor perceptions of reference points and whether interventions—such as personalized benchmarks or behavioral nudges—can help mitigate excessive risk-taking induced by external reference dependence.

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Table I: Summary Statistics

	Mean	SD	p10	p50	p90
Portfolios					
Portfolio lags market	0.576	0.494	0	1	1
Market return–Portfolio return	0.022	0.079	-0.048	0.013	0.051
Portfolio return (3 month)	0.009	0.43	-0.044	0.018	0.052
Portfolio beta (only for stocks and equity funds)	1.18	1.34	0.21	1.07	4.12
Total num. securities in portfolio	14.36	15	1.74	10.26	31.65
Num. stocks in portfolio	4.21	7.58	0.76	2.55	9.15
Share of stocks	0.337	0.358	0	0.168	1
Share of bonds	0.09	0.22	0	0	0.444
Share of mutual funds	0.447	0.375	0	0.427	1
Share of ETFs	0.086	0.151	0	0	0.25
Share of stocks, equity mutual funds, equity ETFs	0.546	0.281	0.093	0.464	1
Portfolios of US households (from SCF)					
Share of stocks	0.355				
Share of bonds	0.061				
Share of pooled investment funds	0.524				
Trades at the account-month level					
Probability to trade	0.129	0.143	0.007	0.092	0.354
Trade size	0.149	0.234	0.003	0.113	0.32
Num. trades	1.96	2.62	0.18	0.85	4.73
Trades at the asset level					
Trade size	0.083	0.205	0.003	0.021	0.238
Salary (NIS) and age, 2022					
Net monthly salary per account	15714	17480	1921	12386	31683
Net monthly salary in Israel per employee	7615			6143	
Age	51	18	34	54	71
Number of account-holders					
One-owner accounts	35.94				
Two-owner accounts	58.03				
Three-owner accounts	4.31				
Four-owner accounts	1.42				
More than four owners	0.3				

Table II: Investor's response to underperforming portfolio

The table presents the results of the panel regressions for the propensity to perform a trade (columns 1 and 2) and trade size of the buy transactions net of sell transactions scaled by the investor's lagged total value of assets in the brokerage account only for months in which the investor performs any trade (columns 3 and 4). *Portfolio lags market* is the main explanatory variable, estimated as a dummy equal to one if the portfolio three-month return lags the corresponding market return, and 0 otherwise. In columns 2 and 4, we control for the three-month return and volatility of the portfolio. In all columns, we include account and year-month fixed effects. Standard errors (in parentheses) are clustered by account. *$p<.1$; **$p<.05$; ***$p<.01$.

	(1)	(2)	(3)	(4)
	Trade		Trade size	
Portfolio lags market	0.038***	0.023***	0.978***	0.693***
	(0.014)	(0.007)	(0.170)	(0.152)
Portfolio return		0.028***		0.496***
		(0.009)		(0.107)
Portfolio volatility		0.002***		0.021***
		(0.000)		(0.006)
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	6,959,263	6,959,263	1,795,490	1,795,490
Adjusted R^2	0.333	0.346	0.329	0.339

Table III: Underperforming portfolio and investor's risk-taking

The table present the results of the panel regressions for the trade size of the buy transactions net of sell transactions scaled by lagged total value of assets in the brokerage account based on Equation 2. The main explanatory variable in columns 1 and 3 of both Panels is a dummy equal to one if the portfolio three-month return lags the corresponding market return, and 0 otherwise. Columns 2 and 4 present the results for the difference between the market and the portfolio returns. *Risky security* is a dummy variable taking the value of 1 if the security is a stock or an equity fund (mutual fund or ETF), and zero if the security is a bond or a bond fund. *High beta security*, an indicator whether the risky security's beta is in the top tercile. In columns 1 and 2, we control for portfolio-level time-varying characteristics as in Equation 1. The security control variables include an indicator whether its return is lower than the portfolio return (columns 1 and 2) and the difference between the security and portfolio three-month returns (columns 3 and 4); the three-month return of the security. We include account, time and security fixed effects in columns 1 and 3, and security and account-time fixed effects in columns 2 and 4. Standard errors (in parentheses) are clustered by account. *$p<.1$; **$p<.05$; ***$p<.01$.

Panel A

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.221***	0.224***		
X Risky security	(0.019)	(0.023)		
Portfolio lags market	0.356***	0.358***		
	(0.032)	(0.035)		
Market return–Portfolio return			0.028***	0.031***
X Risky security			(0.010)	(0.011)
Market return–Portfolio return			0.074***	0.077***
			(0.023)	(0.026)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	83,810,603	73,753,338	83,810,603	73,753,338
Adjusted R^2	0.548	0.859	0.547	0.858

Table III - Continued

Panel B

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.125***	0.129***		
X High beta security	(0.017)	(0.018)		
Portfolio lags market	0.351***	0.359***		
	(0.018)	(0.021)		
Market return–Portfolio return			0.021***	0.024***
X High beta security			(0.007)	(0.009)
Market return–Portfolio return			0.075***	0.079***
			(0.021)	(0.023)
High beta security	0.156	0.161	0.174	0.177
	(0.667)	(0.333)	(0.321)	(0.329)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	55,929,736	49,218,173	55,929,736	49,218,173
Adjusted R^2	0.544	0.856	0.544	0.854

Table IV: Share of Risky Holdings

The table presents the results of the panel regressions at the portfolio level for the share of risky securities in the portfolio (columns 1-3) and the overall beta of the portfolio (columns 4-6) using the specification in Equation 1. We split investors into three groups by the share of holding of risky securities (stocks, equity mutual funds, equity ETFs) out of total holdings. *Portfolio lags market* is a dummy variable equal to one if the portfolio three-month return lags the corresponding market return, and 0 otherwise. The rest of the variables are the same as in Table II. We include account and year-month fixed effects. Standard errors (in parentheses) are clustered by account. *$p < .1$; **$p < .05$; ***$p < .01$.

	%Risky Assets			Portfolio Beta		
	(1)	(2)	(3)	(4)	(5)	(6)
	<30%	30%-60%	>60%	<30%	30%-60%	>60%
Portfolio lags market	0.054***	0.033*	0.011	0.033***	0.025**	0.021***
	(0.021)	(0.018)	(0.012)	(0.013)	(0.011)	(0.008)
Controls	YES	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Observations	1,104,263	930,404	1,589,963	1,104,263	930,404	1,589,963
Adjusted R^2	0.328	0.321	0.320	0.428	0.429	0.433

Table V: Different Periods of the Market

Panel A presents the results of the panel regressions for the trade size of the buy transactions net of sell transactions scaled by lagged total value of assets in the brokerage account based on Equation 2 as in Panel B of Table III, splitting between periods with positive and negative three-month market returns. In Panel A, *High beta security* is a dummy whether the security's beta is in the top tercile. In Panel B, the measure of the security's risk is *High vol security*, an indicator whether the security's return volatility is in the top tercile. Columns 1 and 3 in Panel A, and 2 and 5 in Panel B, include periods with positive market returns. Columns 2 and 4 in Panel A, and 3 and 6 in Panel B, include periods with negative market returns. In both Panels, the rest of the variables are the same as Table III. We include account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. *$p<.1$; **$p<.05$; ***$p<.01$.

Panel A

	Trade Size			
	(1) Market up	(2) Market down	(3) Market up	(4) Market down
Portfolio lags market X High beta security	0.136***	0.111***		
	(0.038)	(0.041)		
Portfolio lags market	0.408***	0.264***		
	(0.021)	(0.025)		
Market return–Portfolio return			0.025***	0.016**
X High beta security			(0.008)	(0.008)
Market return–Portfolio return			0.087***	0.057**
			(0.023)	(0.025)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	35,173,096	20,756,640	35,173,096	20,756,640
Adjusted R^2	0.539	0.572	0.538	0.571

Table V - Continued

Panel B

	Trade Size					
	(1) Full Sample	(2) Market up	(3) Market down	(4) Full Sample	(5) Market up	(6) Market down
Portfolio lags market	0.155***	0.191***	0.102***			
X High vol security	(0.012)	(0.013)	(0.009)			
Portfolio lags market	0.342***	0.438***	0.184***			
	(0.028)	(0.034)	(0.031)			
Market–Portfolio return				0.022***	0.027***	0.016***
X High vol security				(0.002)	(0.005)	(0.002)
Market return–Portfolio				0.073***	0.088***	0.047***
return				(0.010)	(0.021)	(0.013)
Controls	YES	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Security FE	YES	YES	YES	YES	YES	YES
Observations	55,929,736	35,173,096	20,756,640	55,929,736	35,173,096	20,756,640
Adjusted R^2	0.581	0.607	0.720	0.585	0.618	0.719

Table VI: Underperforming vs. outperforming portfolios

Panel A presents the results of the baseline panel regressions for the trade size of the buy transactions net of sell transactions scaled by lagged total value of assets in the brokerage account as in Panel B of Table III based on Equation 2. We perform the analysis using *Security return–Portfolio return*, the difference between the security and portfolio three-month returns, as the explanatory variable, splitting periods when the market outperforms the portfolio (columns 1,3,5) and when the market underperforms the portfolio (columns 2,4,6). Columns 1-2 include the full sample, columns 3 and 4 present only periods with positive three-month market returns, and columns 5 and 6 only the negative ones. We include bank account, time and security fixed effects.
Panel B presents the results of the panel regressions in Equation 1 for the investor's portfolio beta (column 1), whether the portfolio beta is above 1 (column 2), investor's volatility (column 3), and number of securities in the portfolio (column 4). We focus only on a subsample of outperforming investors that previously were underperforming at any point in the past. *Portfolio outperforms market* is a dummy equal to one if the portfolio three-month return currently outperforms the TA35 three-month return, and the portfolio underperformed the market in the past over three-month period. The control variables are as defined in Table II (in columns 3 and 4, we exclude portfolio volatility from the control variables). We include bank account and time fixed effects.
In Panel C, we rerun the specification from Panel B using a rolling five-month window. We redefine *Portfolio outperforms market* as an indicator equal to one if the portfolio underperformed the market over the first three months of the window but outperformed it over the subsequent two months. We restrict the sample to investors whose portfolios exhibit higher cumulative returns than the market, measured from the window's starting point. Similarly, in Panel D, *Portfolio outperforms market* is a dummy whether the portfolio underperformed the market over the first two months of the window but outperformed it over the subsequent three months.
Standard errors (in parentheses) are clustered by account. *$p<.1$; **$p<.05$; ***$p<.01$.

Panel A

	Trade Size					
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Market Up		Market Down	
Market–Portfolio return>0	0.025***		0.031***		0.021***	
X High beta security	(0.003)		(0.008)		(0.005)	
Market–Portfolio return<0		0.012***		0.014***		0.006***
X High beta security		(0.002)		(0.003)		(0.002)
Controls	YES	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Security FE	YES	YES	YES	YES	YES	YES
Observations	35,832,471	20,097,265	21,842,493	13,330,603	13,989,977	6,766,663
Adjusted R^2	0.571	0.538	0.556	0.530	0.588	0.564

Table VI - Continued

Panel B

	(1) Portfolio beta	(2) Portfolio beta>1	(3) Portfolio volatility	(4) Num. securities
Portfolio outperforms market	-0.033***	0.048**	-0.007***	0.021***
	(0.004)	(0.009)	(0.002)	(0.006)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	4,290,942	4,290,942	4,290,942	4,290,942
Adjusted R^2	0.423	0.347	0.416	0.347

Panel C

	(1) Portfolio beta	(2) Portfolio beta>1	(3) Portfolio volatility	(4) Num. securities
Portfolio outperforms market	-0.048**	0.062*	-0.016**	0.037*
(alternative definition 1)	(0.022)	(0.034)	(0.008)	(0.019)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	207,842	207,842	207,842	207,842
Adjusted R^2	0.281	0.219	0.158	0.214

Panel D

	(1) Portfolio beta	(2) Portfolio beta>1	(3) Portfolio volatility	(4) Num. securities
Portfolio outperforms market	-0.041*	0.054	-0.012*	0.033*
(alternative definition 2)	(0.023)	(0.043)	(0.007)	(0.021)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	245,254	245,254	245,254	245,254
Adjusted R^2	0.246	0.195	0.172	0.223

Table VII: Trading Frequency

This table presents the results of the panel regressions for the trade amount of the buy transactions net of sell transactions scaled by lagged portfolio value as in Panel B of Table III based on Equation 2. The sample is split between investors with above-median and below-median trading activity over the past three months. We include bank account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
	Trade Size			
	High Freq.	Low Freq.	High Freq.	Low Freq.
Portfolio lags market	0.134***	0.089***		
X High beta security	(0.042)	(0.033)		
Market return–Portfolio return			0.026***	0.012**
X High beta security			(0.010)	(0.006)
	(0.667)	(0.333)	(0.321)	(0.329)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	43,061,582	12,868,154	43,061,582	12,868,154
Adjusted R^2	0.539	0.538	0.541	0.539

Table VIII: Holiday Gatherings

This table presents the results of the panel regressions for the trade amount of the buy transactions net of sell transactions scaled by lagged portfolio value around Passover based on Equation 2. *After* is a dummy equal to one for the month following the holiday, and zero for the preceding month. The rest of the variables are the same as in Table II. We include bank account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market x After	-0.156**	-0.161**		
	(0.075)	(0.076)		
Portfolio lags market x After		-0.061**		
X High beta security		(0.028)		
Market return–Portfolio return x After			-0.038*	-0.041*
			(0.022)	(0.023)
Market return–Portfolio return x After				-0.018**
X High beta security				(0.008)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	2,352,128	2,352,128	2,352,128	2,352,128
Adjusted R^2	0.378	0.378	0.376	0.376

Table IX: Index reform

This table presents the results of the panel regressions for the trade amount of the buy transactions net of sell transactions scaled by lagged portfolio value around the market index reform based on Equation 2. *After* is a dummy equal to one for the month of the reform and the following month (i.e., February and March 2017), and zero for the preceding two months. *Stock added* is an indicator whether the stock was added to the TA35 or TA125 as part of the reform. The rest of the variables are the same as in Table II. We include bank account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. *$p <.1$; **$p <.05$; ***$p <.01$.

	Trade Size					
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio lags market X After	0.205***	0.238***	0.209***			
	(0.031)	(0.033)	(0.027)			
Portfolio lags market X After X High beta security		0.099***				
		(0.041)				
Portfolio lags market X After X Stock added			0.028***			
			(0.009)			
Market return–Portfolio return X After				0.047***	0.052***	0.050***
				(0.012)	(0.017)	(0.011)
Market return–Portfolio return X After X High beta security					0.026***	
					(0.006)	
Market return–Portfolio return X After X Stock added						0.011***
						(0.004)
Controls	YES	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Security FE	YES	YES	YES	YES	YES	YES
Observations	4,863,455	4,863,455	4,863,455	4,863,455	4,863,455	4,863,455
Adjusted R^2	0.657	0.658	0.657	0.661	0.662	0.661

Table X: Market index saliency

This table presents the results of the panel regressions for the trade size of the buy transactions net of sell transactions scaled by lagged portfolio value based on Equation 2 using alternative market indexes (instead of TA35). All the other variables are the same as in Table II. In Panel A, we use the Nasdaq100 as the market index. In Panel B, we use the S&P500 as the market index in columns 1 and 2 and the MSCI World Index in columns 3 and 4. In Panel C, we use the DAX as the market index in columns 1 and 2, and the FTSE in columns 3 and 4. Columns 3 and 4 in Panel A and all columns in Panels B,C include only accounts with portfolios with above median share of foreign assets. In all Panels, we include account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. Panel D presents the portfolio beta against different market indices. Column 1 includes all investors, in column 2 we focus only on the ones with above median share of foreign securities holdings, while in column 3 we focus only the upper 10th percentile by total account value. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A - Market index: NASDAQ100

	Trade Size			
	(1)	(2)	(3)	(4)
	Full sample		Portfolios with > median foreign assets	
Portfolio lags market (alt)	0.011		0.082***	
X High beta (alt) security	(0.146)		(0.020)	
Portfolio lags market (alt)	0.048		0.147***	
	(0.113)		(0.029)	
Market (alt) return–Portfolio return		0.003		0.015***
X High beta (alt) security		(0.077)		(0.004)
Market (alt) return–Portfolio return		0.010		0.033***
		(0.094)		(0.011)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	55,929,736	55,929,736	7,169,592	7,169,592
Adjusted R^2	0.477	0.474	0.481	0.480

Table X - Continued

Panel B - Market indexes not presented on the platform: S&P500, MSCI

	Trade Size			
	(1)	(2)	(3)	(4)
	S&P500		MSCI World Index	
Portfolio lags market (alt)	0.041*		0.011	
X High beta (alt) security	(0.023)		(0.028)	
Portfolio lags market (alt)	0.101*		0.058	
	(0.056)		(0.072)	
Market (alt) return–Portfolio return		0.011*		0.004
X High beta (alt) security		(0.006)		(0.009)
Market (alt) return–Portfolio return		0.024*		0.015
		(0.013)		(0.018)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	7,169,592	7,169,592	7,169,592	7,169,592
Adjusted R^2	0.474	0.472	0.452	0.450

Panel C - Market indexes not presented on the platform: DAX, FTSE

	Trade Size			
	(1)	(2)	(3)	(4)
	DAX		FTSE	
Portfolio lags market (alt)	0.009		0.011	
X High beta (alt) security	(0.016)		(0.013)	
Portfolio lags market (alt)	0.042		0.049	
	(0.065)		(0.077)	
Market (alt) return–Portfolio return		0.001		0.002
X High beta (alt) security		(0.011)		(0.007)
Market (alt) return–Portfolio return		0.011		0.012
		(0.014)		(0.013)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	7,169,592	7,169,592	7,169,592	7,169,592
Adjusted R^2	0.431	0.429	0.438	0.437

Table X - Continued

Panel D - Portfolio betas against different market indices

	(1) All Investors	(2) High Foreign Holdings	(3) Top Wealth Investors
TA35	1.18	0.94	1.26
S&P500	0.87	1.11	1.18
Nasdaq	0.61	0.54	0.79
MSCI World	0.55	0.42	0.64
MSCI EAFE	0.59	0.48	0.73
FTSE	0.52	0.39	0.59
DAX	0.47	0.33	0.58

Table XI: Alternative explanations

Panels A,B present the results of the panel regressions for the trade size of the buy transactions net of sell transactions scaled by lagged portfolio value as a function of the security's risk based on Equation 2 as in Table III. In Panel A, we include an additional interaction term *Portfolio return X High beta security* as a control variable. In columns 2 and 3, we split between positive vs. negative three-month investor portfolio returns. In column 4, we focus on losing portfolios in periods of negative three-month market returns. In Panel B, we add to the baseline specification the return of the security since its purchase price (column 1), the return from the 52-week high (column 2) and 52-week low (column 3). We include bank account, time and security fixed effects.
Panel C presents the results of the panel regressions at the account level as in Table II, but only for accounts that hold at least one risky asset. The outcome variables are the number securities in portfolio (column 1), portfolio HHI calculated based on number of securities (column 2), portfolio HHI calculated based on security holding amounts (column 3), the overall portfolio beta (column 4) and overall portfolio volatility (column 5). In column 5, we exclude portfolio volatility from the control variables.
In all Panels, standard errors (in parentheses) are clustered by account. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A - Domains of winnings and losses

	Trade Size			
	(1)	(2)	(3)	(4)
	All	Portfolio return>0	Portfolio return<0	Portfolio return<0 & Market return<0
Portfolio lags market	0.109***	0.112***	0.106***	0.108***
X High beta security	(0.022)	(0.029)	(0.021)	(0.023)
Portfolio return	0.203**	0.188***	0.227***	0.209***
X High beta security	(0.032)	(0.035)	(0.034)	(0.039)
Portfolio lags market	0.357***	0.418***	0.262***	0.314***
	(0.054)	(0.056)	(0.051)	(0.077)
Portfolio return	0.523***	0.576***	0.519***	0.547**
	(0.143)	(0.159)	(0.164)	(0.201)
High beta security	0.083	0.106	0.041	0.057
	(0.521)	(1.295)	(0.634)	(0.768)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	55,929,736	32,838,517	23,091,219	7,843,737
Adjusted R^2	0.544	0.576	0.659	0.745

Table XI - Continued

Panel B - Other Reference Points

	Trade Size				
	(1)	(2)	(3)	(4)	(5)
	Incl. Purchase Price	Incl. 52-week High	Incl. 52-week Low	Incl. TA35 52-week High	Incl. TA35 All Time High
Portfolio lags market	0.124***	0.123***	0.123***	0.120***	0.119***
X High beta security	(0.019)	(0.019)	(0.022)	(0.028)	(0.032)
Additional control	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Security FE	YES	YES	YES	YES	YES
Observations	35,584,952	55,929,736	55,929,736	55,929,736	55,929,736
Adjusted R^2	0.544	0.544	0.544	0.547	0.549

Panel C - Diversification and Portfolio Risk

	(1)	(2)	(3)	(4)	(5)
	Num securities	Portfolio HHI (securities)	Portfolio HHI (amounts)	Portfolio Beta	Portfolio Volatility
Portfolio lags market	-0.064***	0.007*	0.007*	0.059**	0.031*
	(0.019)	(0.004)	(0.004)	(0.028)	(0.017)
Controls	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES
Observations	5,084,630	5,084,630	5,084,630	5,084,630	5,084,630
Adjusted R^2	0.306	0.392	0.401	0.427	0.418

Table XII: Alternative explanations - Continued

The table presents the results of the security-level specification based on Equation 2. In Columns 1-3 of Panel A, we change the outcome variable of this specification to the one-month, one-year, and two-year raw returns, respectively. Columns 4-6 present the results for the abnormal returns for the same time-windows. In Panel B, in Column 1 we add to the baseline specification the beta of the stock (beyond the the high-beta indicator), in column 2 the shares of the risky and safe holdings (as defined in Section II.C), and in column 3 the stock overall return since the purchasing date. In column 4, we perform the security-level specification based on Equation 2 with account and security x three-months FEs. In all Panels, standard errors (in parentheses) are clustered by account. *$p<.1$; **$p<.05$; ***$p<.01$.

Panel A - Security Return

	Raw Return			Abnormal Return		
	(1) 1mo	(2) 1yr	(3) 2yrs	(4) 1mo	(5) 1yr	(6) 2yrs
Portfolio lags market X High beta security	0.013 (0.017)	0.049 (0.075)	0.047 (0.081)	-0.004 (0.023)	-0.017 (0.082)	-0.026 (0.094)
Controls	YES	YES	YES	YES	YES	YES
Account FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Security FE	YES	YES	YES	YES	YES	YES
Observations	55,929,736	48,043,641	40,492,729	55,929,736	48,043,641	40,492,729
Adjusted R^2	0.381	0.354	0.351	0.374	0.366	0.357

Panel B - Portfolio Rebalancing and Disposition Effect

	Trade Size			
	(1) Incl. Stock Beta	(2) Incl. Holdings Shares	(3) Incl. Stock Return	(4) Incl. Stock x Time FEs
Portfolio lags market X High beta security	0.128*** (0.017)	0.128*** (0.018)	0.124*** (0.020)	0.119*** (0.022)
Additional control	YES	YES	YES	NO
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	NO
Security FE	YES	YES	YES	NO
Security-3 months FE	NO	NO	NO	YES
Observations	55,929,736	55,929,736	35,584,952	55,238,067
Adjusted R^2	0.543	0.545	0.544	0.811

Table XIII: Robustness tests

This table presents robustness tests for the results of the panel regressions in Table III at the security level. In Panel A, *Portfolio lags market*, *Market return–Portfolio return* and the rest of the variables are calculated over year-to-date instead of three-month period. In Panel B, all the variables are calculated over the preceding 12 months. In Panel C, we use the TA125 as the market index instead of TA35, and adjust the beta to the TA125. The rest of the variables are the same as in Table III. In Panel D, we rerun the specification in Table III only for the years 2014-2019. We include bank account, time and security fixed effects. Panel E presents the results for security skeness as the measure of its risk. In Columns 1 and 2, *High skew security* is an indicator whether the security is in the top tercile of the 3-month return skewness. In columns 3 and 4, we use *High return security*, a dummy if the security is in the top 3-month return tercile. We include bank account, time and security fixed effects in columns 1 and 3 in all Panels, and security and investor-time fixed effects in columns 2 and 4 of every Panel. Standard errors (in parentheses) are clustered by account. *$p < .1$; **$p < .05$; ***$p < .01$.

Panel A - Alternative return period: YTD

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.151***	0.157***		
X High beta security	(0.016)	(0.018)		
Portfolio lags market	0.417***	0.431***		
	(0.013)	(0.015)		
Market return–Portfolio return			0.027***	0.033***
X High beta security			(0.005)	(0.006)
Market return–Portfolio return			0.094***	0.099***
			(0.026)	(0.027)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	48,358,563	42,555,538	48,358,563	42,555,538
Adjusted R^2	0.501	0.844	0.502	0.848

Table XIII - Continued

Panel B - Alternative return period: 12-month

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.133***	0.136***		
X High beta security	(0.024)	(0.026)		
Portfolio lags market	0.377***	0.378***		
	(0.036)	(0.039)		
Market return–Portfolio return			0.023***	0.025***
X High beta security			(0.007)	(0.008)
Market return–Portfolio return			0.081***	0.083**
			(0.034)	(0.037)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	41,812,795	36,794,822	41,812,795	36,794,822
Adjusted R^2	0.528	0.849	0.528	0.849

Panel C - Alternative market index: TA125

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.127***	0.131***		
X High beta security	(0.017)	(0.028)		
Portfolio lags market	0.354***	0.362***		
	(0.014)	(0.027)		
Market return–Portfolio return			0.024***	0.027***
X High beta security			(0.005)	(0.005)
Market return–Portfolio return			0.074***	0.078***
			(0.022)	(0.024)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	55,929,736	49,2018,173	55,929,736	49,2018,173
Adjusted R^2	0.502	0.840	0.501	0.838

Table XIII - Continued

Panel D - Only years 2014-2019

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.123***	0.128***		
X High beta security	(0.023)	(0.025)		
Portfolio lags market	0.351***	0.359***		
	(0.028)	(0.032)		
Market return–Portfolio return			0.020***	0.023**
X High beta security			(0.005)	(0.007)
Market return–Portfolio return			0.076**	0.079**
			(0.026)	(0.027)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	35,422,166	31,171,510	35,422,166	31,171,510
Adjusted R^2	0.583	0.871	0.582	0.872

Panel E - Security skewness

	(1)	(2)	(3)	(4)
	Trade Size			
Portfolio lags market	0.111***	0.113***		
X High skew security	(0.034)	(0.039)		
Portfolio lags market			0.137***	0.140***
X High return security			(0.042)	(0.045)
Controls	YES	YES	YES	YES
Account FE	YES		YES	
Date FE	YES		YES	
Security FE	YES	YES	YES	YES
Account-date FE		YES		YES
Observations	55,929,736	49,218,173	55,929,736	49,218,173
Adjusted R^2	0.511	0.802	0.524	0.813