FOMO Economics: External Reference-Dependence 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 the 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 "market," 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, and does not reverse when individual portfolios are ahead of the market. Our evidence provides a novel perspective on the individual investors' demand for risky assets.

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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. 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 market index. Investors whose portfolios underperform the market trade more frequently and in larger volumes, with a nearly 13 percent increase in trading propensity for every percentage point of underperformance. 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 are 15% more likely to buy risky securities and 9% more likely to purchase high-beta stocks, 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. Investors are also 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.

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 must be accessible and 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, suggesting that heightened index visibility led to greater investor attention and trading responses.

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.

This paper builds on and contributes to several different strands of the literature. There is a large experimental literature showing that individual risk-taking is consistent with S-shapred preferences around a "social" reference point. Frydman (2015) 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. He shows that a higher return by the peer is perceived as particularly unpleasant, suggesting a desire to "keep up with the Joneses." Kirchler and Kirchler (2024) find in an experiment that social reference points shape decisions under uncertainty, where high social reference point decreases risk aversion significantly, especially when peer earnings are salient. Similarly, Schwerter (2024) investigate the consequences of social reference points for risk taking in a laboratory experiment and find that individuals make less risk-averse choices in the case of larger peers' earnings. Kirchler, Lindner, and Weitzel (2018) find that both rank and tournament incentives increase risk-taking among underperforming finance professionals.

Our evidence points to the importance of "local" peer wealth as the relevant reference point. DeMarzo, Kaniel, and Kremer (2004) develop a model in which borrowing constraints lead individuals endowed with local resources to compete for local resources through their portfolio choices and herd into risky portfolios that are biased towards local assets rather than diversifying their portfolios more broadly, consistent with our evidence of agents reacting to their "local" market index rather than the "global" ones. Hong, Jiang, Wang, and Zhao (2014) show that status concerns lead retail investors to excessively trade small local stocks, especially when their peers are wealthier on average (holding own wealth constant), and argue that their evidence supports the idea of "keeping up the with the Joneses."

Our findings also contribute to the literature on different reference points that are used by investors, as well as for other applications such as negotiations, M&As 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., Peng and Xiong (2006)). We show that retail investors use the market as a salient reference point, potentially impacting prices of the securities they trade.

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 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 acting as an "aspiration" level. Similarly, Bali, Gunaydin, Jansson, and Karabulut (2023) social status concerns combined with the lottery-type preferences of rich households 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 retail investors from one of the leading financial institutions in Israel. The data includes the non-retirement portfolios[1] 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, 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 each 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

[1]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.

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 TA-35 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 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, foreign residents purchased equity holdings in a net amount of US$3.9 billion on TASE, following purchases in a similar amount in 2021 (Bank of Israel).

Around 30% of the companies composing the TA35 are traded in another stock market (dual 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 exchanges like NASDAQ, NYSE and London Stock exchange. This allows them to access a broader investor base and more significant capital markets. The biggest company by market capitalization traded on TASE is the international pharmaceutical company "Teva".

II.C Variable Definitions

In this paper, our focus is on the performance of the portfolio relative to the market. There is no specific time window that was found in the literature as the most relevant for retail investors when assessing their performance. Thus, we use a three-month time window across all the variables, and conduct robustness to show that the results hold also with two different time windows, namely year-to-date and preceding 12 months.

We estimate this relative underperformance in two ways. First, we use a dummy equals 1 if the portfolio 3-month return lags the corresponding TA35 return, and 0 otherwise. As an alternative measure, we use a continuous variable calculated as the difference between the TA35 and the portfolio returns.

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 3 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.

The dependent variable in the account-level specifications is an indicator whether the investor conducts any trade in a given month. The main outcome variable in the security level specifications is the trade size of the security scaled by the investor's lagged non-retirement financial assets. We also use a dummy variable taking the value of 1 for buy transactions and zero for sell.

In all our specifications, we control for portfolio-level time-varying changes, namely the 3-month return and the 3-month volatility. The portfolio's volatility is calculated using daily data over 3 months ending at month *t-1*.

At the security level, we also control whether the security return is lower than the portfolio return, and when we use the continuous measure for underperforming portfolios we control for the difference between the security and portfolio returns; the 3-month return of the security and whether the security has high beta.

The probability to trade is about 13%, meaning that each account trades about 2 months a year.

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

In this section we analyze the response of investors to their portfolio perfomance relative to that of the market, in particular, we investigate their propensity to trade (section III.A) and the effect of relative underperfomance on risk-taking (section III.B). Then, in section III.C we show that this response is asymmetric.

III.A The Effect on Trading Propensity

We start the analysis by exploring how investors respond when their portfolios lag the market. To this end, we perform the following account-level specification:

$$\text{Trade}_{it} = \beta_1 \text{Relative Underperformance}_{it} + \beta_2 \text{Controls}_{it} + \alpha_i + \alpha_t + \varepsilon_{it}, \qquad (1)$$

where the outcome variable, *Trade* is an indicator whether investor i conducts any trade in month t. We estimate underperformance relative to the market in two ways. First, we use *Portfolio lags market*, a dummy equals 1 if the portfolio return lags the corresponding TA35 return, and 0 otherwise. As an alternative measure, we use a continuous variable *Market return–Portfolio return*, calculated as the difference between the TA35 and the portfolio returns. We control for portfolio-level time-varying changes, namely the cumulative investor's return and its 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.

Columns 1-2 present in Table II presents the results for this specification. In Column 1 we use the indicator as the estimate of the portfolio's relative underperformance, in Column 2 we use the continuous variable. The coefficients are positive and statistically significant in both columns. The economic magnitudes are meaningful. Investors with underperforming portfolios are 17.9% more likely to conduct a trade compared to investors that outperform the market (relative to the sample mean). An additional one percentage point difference between the market and the portfolio returns is associated with 12.7% higher propensity to trade, relative to the sample mean.

In Columns 3-4 of Table II, we study trade size. Here, we focus on months in which the investor performs any trade and find that underperforming portfolios lead to 4.6%

higher trade volumes (relative to the sample mean). An additional one percentage point difference between the market and the portfolio returns is associated with 1.8% higher volumes, relative to the sample mean.

These results provide first evidence that investors refer to the market portfolio as a reference point when evaluating their performance, beyond other affecting factors. Investors lagging the market are more likely to trade, with larger amounts, relative to investors the outperform the market. In the next section, we turn to show how they adjust their portfolios to keep up with the market. We analyze their buy and sell transactions and the riskiness of the portfolios.

III.B The Effect on Investor's Risk-Taking

To analyze how relative underperforming portfolio affects the risk-taking of the investor, we utilize the granularity of the dataset and perform the following security-level baseline specification:

$$\begin{aligned} \mathrm{Y}_{ist} =& \beta_1 \text{Relative Underperformance}_{it} \times \text{High beta security}_{st} + \beta_2 \text{Controls}_{st} \\ &+ \beta_3 \text{Controls}_{it} + \alpha_i + \alpha_s + \alpha_t + \varepsilon_{ist}. \end{aligned} \tag{2}$$

Here Y stands for different outcome variables. First, we use a dummy variable taking the value of 1 for buy transactions and zero for sell. Next, we study the effect on the trade size of security s in account i on date t, scaled by the investor's lagged non-retirement financial assets. We estimate the riskiness of the security with *Risky security*, a dummy variable equals 1 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 *High beta security*, an indicator whether the beta of the security is in the top tercile. The security's beta is calculated using daily data over 3 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 add to the specification in Equation 1 these riskiness variables, as well as the interactions with *Relative Underperformance* measures. We control for portfolio-level time-varying characteristics as in Equation 1. We include the following security-level time varying control variables: an indicator whether the security return is lower than the portfolio return, and when we use the alternative measure for underperforming portfolios we add the difference between the security and portfolio returns; and the 3-month cumulative return of the security. α_i is the account-fixed effect, α_s is the security fixed effect that accounts for time-invariant asset-specific characteristics (such as prominence, firm characteristics, industry and media coverage), α_t is the date-fixed effect that controls for the macro and market factors that influence all individuals on a given date.[2] Standard errors are clustered by account.

Panels A,B in Table III present the results for the propensity to purchase the security. In Panel A, we use *Security lags Portfolio* and interact it with the riskiness measures, while in Panel B we use the continuous variable *Security return–Portfolio return.* In both Panels, Columns 1,3 include account, security and time fixed effects, Columns 2,4 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.

Analyzing the interaction terms in Panel A, we find that they are positive and significant in all columns, meaning that investors increase risk in response to underperforming portfolios. Investors with portfolios lagging the market are 15.3% more likely to purchase a risky security (relative to the sample mean) compared to investors with outperforming portfolios (Column 2). Focusing only on risky assets, investors with underperforming portfolios have 9.2% higher propensity to purchase a security with higher beta (Column 4).

Panel B shows similar results when using *Security return–Portfolio return* as the rela-

[2]All the results in this specification and the rest of the empirical tests hold when including year-month instead of date fixed effect.

tive underperformance measure. A rise of one percentage point in the difference between the market and the portfolio returns is associated with 10.8% higher likelihood to purchase a risky security (Column 2), and among risky securities, a 6.9% higher probability for purchasing an asset with higher beta (Column 4).

Most of the literature so far has focused on the effects of the prospect theory and reference point on sales, such as the disposition effect, and its effects on the stock market (e.g., Frazzini (2006); Shefrin and Statman (1985)). Thus, our result that investors are buying risky securities and sell safer ones contributes to a more holistic understanding of how the market—as a reference point—affects investor's overall changes to her portfolio.

In Panel C of Table III, we turn to analyze the effect of underperforming portfolios on the trade size. Here, we also find meaningful magnitudes, although smaller than in Panels A,B. 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).

The economic magnitudes for the trade size are larger if we focus only on buy transactions. However, our aim in this paper is to show the overall effect, thus in the rest of the specifications we do not distinguish between buy and sell transactions. Further, in the robustness tests, we verify that the results hold for an alternative return periods (YTD and 12 months instead of 3 months), when using a different common index for the market return (TA125 instead of TA35), and after excluding the COVID period as wealth accumulation of the wealthy investors during this period might affect their trading behavior.

Next, we turn to analyze how the share of risky holdings (stocks, equity mutual funds and ETFs) affects investor's response to underperforming portfolios. To this end, we split investors into three bins, namely below 30%, 30%-60% and above 60%. Performing the security-level specification in Equation 2 in Columns 1-3 of Panel A in Table IV, we

find that investors with underperforming portfolios relative to the market have a similar probability to purchase a risky security in all the groups. The coefficients are similar to the baseline result in Column 1 of Table III. Exploring the propensity to purchase a security with higher beta, we find in Columns 4-6 that investors in the latter group are about twice as much more likely to do it compared to the former ones. These results indicate that all investors increase the riskiness of their portfolios when they lag the market, but it happens gradually. Investors seem to start with increasing their exposure to risky assets first, and then they expand into assets with higher betas.

In Panel B of Table IV, we perform the analysis at the portfolio level in Equation 1 splitting between the three bins, and changing the outcome variable to the share of risky assets (Columns 1-3) and the portfolio's overall beta (Columns 4-6). We find that both the share of risky assets and the portfolio beta increase the most in the below 30% group, meaning that these adjustments to the portfilios leave significant marks on the overall composition of their portfolios.

III.C Asymmetric Effect

Next, we investigate whether the response of investors to the market is symmetric. To this end, we first explore if underperforming investors increase risk in specific periods or whether the effect holds more broadly. Splitting between periods with positive and negative market returns, we find in 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. This indicates that in bull market periods investors are more likely to feel behind missing the high market returns. To keep up with the market, they trade more and specifically increase their exposure to riskier assets. When the investor's portfolio lags the market in bearish periods, both the standalone effect, as well as the corresponding increase in risk, hold although with lower magnitudes.

The fact that the results are not limited to specific periods in the market also help us address alternative explanations that changes in risk-aversion or other related factors could explain the results, rather than the market portfolio as a reference point (as discussed more in details in section V.A).

Our results remain similar when changing the measure of security risk from the systematic component to the overall risk. Panel B of Table V, presents the results for the specification in Equation 2, using the security volatility as the measure of security risk.

Next, we turn to investigate whether the investor's response is symmetric for underperforming vs. outperforming portfolios relative to the market. In Panel A of Table VI, we provide evidence that the behavior is asymmetric. Specifically, we split between periods in which the market outperforms the portfolio from periods when the it underperforms the investor's portfolio. In Columns 1-2, we include the whole sample, in Columns 3-4 we present the results only when the 3-month market return is positive, and in Columns 5-6 only for negative market returns. We find that the effect for underperforming portfolios is more than twofold stronger than the outperforming ones. This indicates that the changes in the risk of investors' portfolios are more moderate for outperforming portfolios, relative to the underperforming ones. The convex risk-adjustment for underperforming portfolios and the concave for the outperforming ones holds across different market conditions, i.e., when the market goes up and down. This is consistent with loss aversion function of (Kahneman and Tversky, 1979), convex in the domain of losses and concave in gains.

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 would not decrease risk at all), it indicates of an asymmetric response.

To this end, we focus on the risk characteristics of their portfolios using the account-

level specification in equation 1 changing the main explanatory variable to *Portfolio outperforms market*, an indicator whether the portfolio return exceeds the market return, and in the past the portfolio underperformed the market. The outcome variables are the portfolio's overall beta, overall volatility, and the number of stocks 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 reduce the riskiness in their portfolios, both the beta and the volatility, and increase the number of the different securities held. However, comparing the magnitudes to the results in Panels B,C of Table IX in section V.C—where we use the same outcome variables to conduct the portfolio-level analysis for the full sample of investors—here we find smaller effects, indicating of the asymmetric behavior of the investors.

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 back once they reach the goal.

IV Market Index Saliency

In previous section 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 in the U.S., 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 their actual holdings. This makes the comparison between the performance of the investor and the market straightforward. However, to do that the investor has to log in to the

platform.

To show that market saliency affects 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

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, expand public holdings in the leading indexes, and increase 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, claiming that it led to higher saliency and investor attention to the updated market indexes. As supporting evidence, we indeed find in our data elevated total trading volumes in February and March 2017.

Importantly, the technical change in the composition of the indexes did not affect their

returns on the first trading day after the reform. The value of the updated index was adjusted to the value of the original one at the end the preceding trading day.

To analyze the effect of market index saliency, we focus on a narrow time window around the end of the implementation of the 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 1 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 VII presents the results of this specification. In Column 2, we add the triple interaction of *Portfolio lags market* with the *After* indicator and with *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 trading volume of the sample mean in high-beta securities (Column 2). This effect is similar, although a bit smaller, to the results in the baseline specification in Panel C 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 1 for the added stocks to the TA35 or TA125. Here, we find that investors with portfolios lagging the market trade more 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 C 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 VIII presents the results. For the full sample of investors (Columns 1-2), 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 investors trade riskier securities when their portfolios lag the Nasdaq100. Comparing the magnitudes to the results in Columns 1,3 in Panel C 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 VIII, even focusing only on investors with above median share of foreign securities holdings. In Columns 1-2, 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 Column 3-4, when using the MSCI as the market index, we find no results.

Finally, in Panel C, we further verify that other indexes do not serve as reference points. Changing the market index to DAX (Columns 1-2) and FTSE (Columns 3-4)—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.

Overall, the results in this section indicate that market index saliency and visibility are important. Between different salient market indexes, only the ones perceived as relevant affect investor's behavior, while other indexes—even the most appropriate ones—that are not presented, have no significant effect.

V Alternative Explanations

In the previous sections, we showed that when investors lag the market index, they increase trading of riskier securities. We provided empirical evidence that the market serves as a salient reference point, thus investors adjust their holdings based on whether the portfolio lags it or not. In this section, we turn to discuss alternative explanations to the results. First, in Section V.A, we discuss that changes in investor's risk aversion and overconfidence cannot fully explain the observed effects. Section V.B shows that the observed effect of the market holds beyond other reference points that were found in the literature. Finally, in Section V.C we provide evidence that investor's learning is not the main effect behind the results. Section V.E provides additional robustness tests.

V.A Risk Aversion

The first concern with the observed effect is that investor's risk-taking is correlated with changes in risk-aversion and overconfidence. 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, if this were indeed the main channel, we would expect to find the rise in riskiness for outperforming portfolios—consistent with the heightened overconfidence—not for underperforming ones. However, when we split in Section III.B between periods with positive and negative market returns, we find the effect holds in both. 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 in Equation 2 an interaction between the portfolio's return with the *High beta security* indicator. The idea is to capture any variation in the investor's 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 IX 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 the risk-aversion indeed plays an important role in the investor's trading behavior, but our results hold beyond this effect.

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 cintinue with the specification in Column 1 of Panel A in Table IX, but this time, each month we split between investors with positive and negative portfolio returns (Columns 2,3 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 similar for portfolios with negative return 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, namely the purchase price (Grinblatt and Han, 2005), the 52-week high or low price (George and Hwang, 2004; Huddart, Lang, and Yetman, 2009). 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 IX presents the results. In column 1, we add the cumulative return of the security (only for which were purchased during our sample period). In columns 2,3 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.

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 4-5 of Panel B in Table IX 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 portfolios 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. In this case, the observed effect captures this learning effect.

We address this concern in Panels C,D of Table IX by showing that investors actually do not diversify their portfolios. In Panel C, we perform the account-level specification in Equation 1 for the full sample of investors, changing the left-hand side variable to the number of securities held in the portfolio (Columns 1,2), portfolio's HHI calculated based on the number of securities (Columns 3,4), and portfolio's HHI calculated based on the holding amounts (Columns 5,6). 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 Panel D, we rerun this specification for the portfolio beta as the outcome variable (Columns 1,2) and portfolio volatility (Columns 3,4). Consistent with the higher concentration, the riskiness of the portfolios goes up, not down, for investors lagging the market.

V.D Investor Characteristics

In this section, we show that investors that are more likely to follow the performance of their portfolios and the market, also engage more in riskier trading once their portfolios lag the market. Specifically, we follow past literature and distinguish between investors based on their degree of financial sophistication, and having the means to trade. To this

end, we use various socio-economic characteristics of the individuals in our sample.

Table X presents the results of this analysis. We perform our baseline security-level specification in Equation 2, splitting between above and below median investors by wealth (Panel A) and salary (Panel B) as observed in the dataset. In Panel C, we split between above and below median municipalities by the municipality's level of education (based on data from the Israel Central Bureau of Statistics). In Panel D, we include only individuals whose occupation appears in the financial institution's records and the ones that are non-retired, and split between white and blue collar occupations. In line with our expectations, we find wealthier and more educated investors respond more when their portfolios lag the market. This is consistent with Aristidou, Giga, Lee, and Zapatero (2022) that show that aspirational utility can drive the demand for riskier assets.

In Panel E, we support this result by showing a univariate comparison between accounts with above vs. below median wealth. Wealthier individuals indeed trade more.

V.E Additional Robustness Tests

In this section, we verify that the results hold for alternative return periods—YTD instead of 3 months (Panel A in Table XI), and a rolling time-window of the preceding 12 months (Panel B). Then, we show that the results remain consistent for a different common index for the market return, TA125 instead of TA35 (Panel C in Table XI). Finally, as wealth accumulation of the wealthy investors during the COVID period might affect their trading behavior differently from other investors and differently from other periods, we exclude this period from the analysis and show that the results remain consistent (Panel D in Table XI).

VI 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 fall 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 assets in portfolio	14.36	15	1.74	10.26	31.65
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 per account (monthly)					
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
Total num. trades	1.96	2.62	0.18	0.85	4.73
Total num. buy trades	1.03	0.94	0	0.5	2
Trade size (asset level)	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 1,2) and trade size scaled by the investor's lagged non-retirement financial assets only for months in which the investor performs any trade (columns 3,4). *Portfolio lags market* is the main explanatory variable in Columns 1,3, a dummy variable equals 1 if the portfolio 3-month return lags the corresponding market return, and 0 otherwise. Columns 2,4 present the results for *Market return–Portfolio return* as the main explanatory variable, the difference between the 3-month market and the portfolio returns. In all the Columns, we control for the 3-month return and volatility of the portfolio. 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	0.023***		0.693***	
	(0.007)		(0.152)	
Market return–Portfolio return		0.004***		0.264***
		(0.001)		(0.083)
Portfolio return	0.028***	0.026***	0.496***	0.509***
	(0.009)	(0.008)	(0.107)	(0.103)
Portfolio volatility	0.002***	0.003***	0.021***	0.019***
	(0.000)	(0.001)	(0.006)	(0.006)
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	6,959,263	6,959,263	3,624,630	3,624,630
Adjusted R^2	.346	.347	.339	.339

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

Panels A,B present the results of the panel regressions for an indicator whether the investor purchases or sells the security. The main explanatory variable in Panel A is a dummy equals 1 if the portfolio 3-month return lags the corresponding market return, and 0 otherwise. In Panel B the main explanatory variable is the difference between the market and the portfolio returns. In Panel C, the outcome variable is the trade size scaled by lagged non-retirement financial assets. The main explanatory variable in Columns 1,3 is a dummy equals 1 if the portfolio 3-month return lags the corresponding market return, and 0 otherwise. Columns 2,4 present the results for the difference between the market and the portfolio returns. In all Panels, *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. The control variables: an indicator whether the security return is lower than the portfolio return (Columns 1,2) and the difference between the security and portfolio 3-month returns (Columns 3,4); the 3-month return of the security. We include account, time and security fixed effects in Columns 1,3, and security and account-time fixed effects in Columns 2,4. Standard errors (in parentheses) are clustered by account. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A

	(1)	(2)	(3)	(4)
	Buy			
Portfolio lags market	0.078***	0.080***		
X Risky security	(0.017)	(0.018)		
Portfolio lags market			0.045***	0.048***
X High beta security			(0.007)	(0.009)
Portfolio lags market	0.152***	0.156***	0.155***	0.151***
	(0.018)	(0.021)	(0.029)	(0.031)
High beta security	0.136	0.131	0.134	0.137
	(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	83,810,603	73,753,338	55,929,736	49,218,173
Adjusted R^2	.584	.838	.584	.832

Table III - Continued

Panel B

	(1)	(2)	(3)	(4)
	Buy			
Market return–Portfolio return	0.054***	0.057***		
X Risky security	(0.017)	(0.018)		
Market return–Portfolio return			0.035***	0.036***
X High beta security			(0.007)	(0.009)
Market return–Portfolio return	0.048***	0.049***	0.052***	0.045***
	(0.018)	(0.019)	(0.020)	(0.013)
High beta security	0.136	0.131	0.134	0.137
	(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	83,810,603	73,753,338	55,929,736	49,218,173
Adjusted R^2	.584	.838	.584	.832

Panel C

	(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	.544	.856	.544	.854

Table IV: Share of Risky Holdings

Panel A presents the results of the panel regressions at the security level for an indicator whether the investor purchases or sells the security as in Table III. We split investors into three groups by their share of holding of risky securities (stocks, equity mutual funds, equity ETFs) out of total holdings. *Portfolio lags market* is a dummy variable equals 1 if the portfolio 3-month return lags the corresponding market return, and 0 otherwise. *Risky security* is a dummy variable taking the value of 1 if the security is risky, 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. We include account, time and security fixed effects. Panel B 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 beta of the portfolio (Columns 4-6). The rest of the variables are the same as in Table II. We include account and year-month fixed effects. In both Panels, standard errors (in parentheses) are clustered by account. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A

	Buy					
	(1)	(2)	(3)	(4)	(5)	(6)
	<30%	30%-60%	>60%	<30%	30%-60%	>60%
Portfolio lags market	0.08***	0.079***	0.076***			
X Risky security	(0.018)	(0.017)	(0.015)			
Portfolio lags market				0.027*	0.042**	0.061***
X High beta security				(0.015)	(0.021)	(0.020)
Portfolio lags market	0.149***	0.150***	0.153***	0.159***	0.154***	0.152***
	(0.027)	(0.026)	(0.021)	(0.036)	(0.034)	(0.031)
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	18,643,245	13,423,137	23,863,354	18,643,245	13,423,137	23,863,354
Adjusted R^2	.585	.585	.587	.585	.586	.589

Panel B

	%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	1,098,263	924,404	1,583,963	1,098,263	924,404	1,583,963
Adjusted R^2	.328	.321	.320	.428	.429	.433

Table V: Different Periods of the Market

Panel A presents the results of the panel regressions for the trade size scaled by lagged non-retirement financial assets splitting between periods with positive vs. negative 3-month market returns. *High beta security*, 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 1,3 in Panel A and 2,5 in Panel B include only periods with positive market returns. Columns 2,4 in Panel A and 3,6 in Panel B include only 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)	(2)	(3)	(4)
	Market up	Market down	Market up	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	.539	.572	.538	.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	.581	.607	.720	.585	.618	.719

Table VI: Underperforming vs. outperforming portfolios

Panel A presents the results of the baseline panel regressions in Equation 2 for the transaction amount scaled by lagged portfolio value as a function of the security's risk. We perform the specification only for securities. The variables are the same as Table II, but here we perform the analysis only with one explanatory variable – *Security return–Portfolio return*, the difference between the security and portfolio 3-month returns. Columns 1-2 include the full sample, Columns 3-4 presents only periods with positive 3-month market returns, and Columns 5-6 only negative ones. We split between differences in the market and the portfolio returns in periods the market outperforms the portfolio (Columns 1,3,5) and periods the market underperforms the portfolio (Columns 2,4,6). 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 1-2), investor's volatility (Columns 3-4), and number of securities in the portfolio (Columns 5-6). We focus only on a subsample of outperforming investors that previously were underperforming. *Portfolio outperforms market* is a dummy equals 1 if the portfolio 3-month return outperforms the TA35 3-month return and the portfolio underperformed the market in the past. *Market return–Portfolio return* and the control variables are as defined in Table II. We include bank account and time fixed effects.
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	.571	.538	.556	.530	.588	.564

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
	Portfolio beta		Portfolio volatility		Num. securities	
Portfolio outperforms market	-0.013***		-0.007***		0.021***	
	(0.004)		(0.002)		(0.006)	
Market return–Portfolio return		-0.002**		-0.002*		0.003**
		(0.001)		(0.001)		(0.001)
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	407,771	407,771	407,771	407,771	407,771	407,771
Adjusted R^2	.423	.421	.416	.414	.304	.302

Table VII: Index reform

This table presents the results of the panel regressions for the transaction amount scaled by lagged portfolio value around the market index reform. *After* is a dummy equal 1 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	0.205***	0.238***	0.209***			
X After	(0.031)	(0.033)	(0.027)			
Portfolio lags market		0.099***				
X After X High beta security		(0.041)				
Portfolio lags market			0.028***			
X After X Stock added			(0.009)			
Market return–Portfolio return				0.047***	0.052***	0.050***
X After				(0.012)	(0.017)	(0.011)
Market return–Portfolio return					0.026***	
X After X High beta security					(0.006)	
Market return–Portfolio return						0.011***
X After X Stock added						(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	.657	.658	.657	.661	.662	.661

Table VIII: Market index saliency

This table presents the results of the panel regressions for the transaction amount scaled by lagged portfolio value 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 1-2 and the MSCI World Index in Columns 3-4. In Panel C, we use the DAX as the market index in Columns 1-2, and the FTSE in Columns 3-4. Columns 3-4 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. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A - Market index: NASDAQ100

	Trade Size			
	(1)	(2)	(3)	(4)
	Full sample		Portfolios with> 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	.477	.474	.481	.480

Table VIII - 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	.474	.472	.452	.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	.431	.429	.438	.437

Table IX: Alternative explanations

Panels A,B present the results of the panel regressions for the transaction amount scaled by lagged portfolio value as a function of the security's risk 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 2,3, we split between positive vs. negative 3-month investor portfolio returns. In Column 4, we focus on losing portfolios in periods of negative 3-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. Panels C,D present the results of the panel regressions at the account level. In Columns 1,3,5, the main explanatory variable is *Portfolio lags market* and in Columns 2,4,6, the main explanatory variable is *Market return–Portfolio return*, as defined in Table II. In Panel C, the outcome variables are the number securities in portfolio (Columns 1,2), portfolio HHI calculated based on number of securities (Columns 3,4), portfolio HHI calculated based on security holding amounts (Columns 5,6). The control variables include the portfolio's return and beta, as well as the wealth and salary of the investor. In Panel D, the dependent variables are the portfolio beta (Columns 1,2) and portfolio volatility (Columns 3,4). The control variables are the same as Panel B, excluding portfolio beta. 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	.544	.576	.659	.745

Table IX - 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	.544	.544	.544	.547	.549

Panel C - Diversification

	(1)	(2)	(3)	(4)	(5)	(6)
	Num securities in portfolio		Portfolio HHI (num. securities)		Portfolio HHI (holding amounts)	
Portfolio lags market	-0.064***		0.007*		0.007*	
	(0.019)		(0.004)		(0.004)	
Market return–Portfolio return		-0.013**		0.002**		0.002
		(0.006)		(0.001)		(0.002)
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	3,624,630	3,624,630	3,624,630	3,624,630	3,624,630	3,624,630
Adjusted R^2	.306	.304	.392	.391	.401	.397

Panel D - Portfolio risk

	(1)	(2)	(3)	(4)
	Portfolio beta		Portfolio volatility	
Portfolio lags market	0.031**		0.018*	
	(0.014)		(0.010)	
Market return–Portfolio return		0.007**		0.004*
		(0.003)		(0.002)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observations	3,624,630	3,624,630	3,624,630	3,624,630
Adjusted R^2	.427	.424	.418	.417

Table X: Investor characteristics

The table presents the results of the panel regressions (as in Table II) as a function of the investor's characteristics. In Panels A and B, we split between above and below median accounts by wealth and salary, respectively. In Panel C, we split between above and below median municipalities by the municipality's level of education (based on data from the Israel Central Bureau of Statistics). In Panel D, we include only individuals whose occupation appears in the bank's records and the ones that are non-retired. We include bank account, time and security fixed effects. Standard errors (in parentheses) are clustered by account. Panel E presents a univariate comparison between accounts with above vs. below median wealth. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Panel A

	Trade Size			
	(1)	(2)	(3)	(4)
	Higher wealth investors		Lower wealth investors	
Portfolio lags market X High beta security	0.178***		0.054*	
	(0.027)		(0.031)	
Market return–Portfolio return		0.036**		0.005*
X High beta security		(0.016)		(0.003)
Portfolio lags market	0.513***		0.129***	
	(0.037)		(0.033)	
Market return–Portfolio return		0.119***		0.021**
		(0.027)		(0.033)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	32,998,544	32,998,544	22,931,192	22,931,192
Adjusted R^2	.526	.525	.538	.538

Table X - Continued

Panel B

	Trade Size			
	(1)	(2)	(3)	(4)
	Higher salary investors		Lower salary investors	
Portfolio lags market X High beta security	0.173***		0.064*	
	(0.019)		(0.037)	
Market return–Portfolio return		0.033***		0.008
X High beta security		(0.007)		(0.009)
Portfolio lags market	0.448***		0.183***	
	(0.031)		(0.036)	
Market return–Portfolio return		0.083***		0.064**
		(0.027)		(0.031)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	32,038,322	32,038,322	23,891,414	23,891,414
Adjusted R^2	.553	.552	.547	.546

Panel C

	Trade Size			
	(1)	(2)	(3)	(4)
	Higher education munis		Lower education munis	
Portfolio lags market X High beta security	0.179***		0.062*	
	(0.018)		(0.033)	
Market return–Portfolio return		0.031***		0.010**
X High beta security		(0.004)		(0.005)
Portfolio lags market	0.461***		0.227***	
	(0.018)		(0.022)	
Market return–Portfolio return		0.078***		0.071*
		(0.022)		(0.041)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	29,880,324	29,880,324	26,049,412	26,049,412
Adjusted R^2	.509	.508	.502	.500

Table X - Continued

Panel D

	Trade Size			
	(1)	(2)	(3)	(4)
	White collar occupations		Blue collar occupations	
Portfolio lags market X High beta security	0.164***		0.079	
	(0.023)		(0.023)	
Market return–Portfolio return		0.028***		0.014
X High beta security		(0.005)		(0.007)
Portfolio lags market	0.439***		0.248*	
	(0.151)		(0.139)	
Market return–Portfolio return		0.078***		0.071
		(0.018)		(0.058)
Controls	YES	YES	YES	YES
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Security FE	YES	YES	YES	YES
Observations	23,993,864	23,993,864	19,631,330	19,631,330
Adjusted R^2	.526	.521	.399	.398

Panel E

	Above median	Below median	High-low
Annual num. trades of securities	21.02	17.46	3.56***
			(0.368)
Num. securities in portfolio	3.82	3.10	0.72***
			(0.001)
Portfolio HHI (by num. securities)	0.52	0.63	-0.11***
			(0.003)
Portfolio HHI (by holding amounts)	0.53	0.65	-0.12***
			(0.002)
Portfolio beta	0.03	0.08	-0.05***
			(0.014)

Table XI: Robustness tests

This table presents robustness tests for the results of the panel regressions in Table II. In Panel A, *Portfolio lags market*, *Market return–Portfolio return* and the rest of the variables are calculated over year-to-date instead of 3-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 Table 2. In Panel D we rerun the specification in Table 2 only for the years 2014-2019. We include bank account, time and security fixed effects. We include bank account, time and security fixed effects in Columns 1,3 in all Panels, and security and investor-time fixed effects in Columns 2,4 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	.501	.844	.502	.848

Table XI - 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	.528	.849	.528	.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	.502	.840	.501	.838

Table XI - 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	.583	.871	.582	.872