

Retail demand and the pricing associated with extreme losses

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September 25, 2025

Abstract

The pricing of extreme negative returns remains a contested issue in behavioral asset pricing. While some investors may extrapolate past performance into the future and demand a premium for bearing downside risk, others may hold on to or even accumulate losing stocks, resulting in overvaluation. Yet, whether retail investors are net buyers or sellers after sharp losses remains an open question. In this paper, contrary to the recent evidence for U.S. markets, we observe that stocks experiencing the most extreme daily losses (*MIN*) in Borsa Istanbul earn statistically and economically significantly lower future returns. Our findings, however, are in line with the systematic overpricing of left-tail risk. The *MIN* discount becomes more pronounced under short-selling restrictions, potentially due to limits to arbitrage. Moreover, leveraging daily portfolios of 20,000 investors, we provide evidence that Turkish retail investors, on average, are net buyers following minimum return days, particularly for stocks with the most extreme negative returns (*High* – *MIN* stocks). This behavior, driven primarily by young, male, domestic, and less diversified investors, may reinforce the persistence of overvaluation. Our results, therefore, offer a potential mechanism for the left-tail risk anomaly in equity markets, particularly pronounced on stocks with high retail investor participation.

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1 Introduction

This paper examines the systematic pricing of extreme negative returns in the cross-section, or the “*MIN* effect”, along with retail investor response to minimum return days. Pricing of extreme negative returns is an active debate. Investors can respond differently to sharp downside movements, and these responses have distinct implications for how such returns are reflected in equity prices.

On the one hand, the safety-first principle suggests that investors prioritize minimizing the probability of an extreme negative return rather than maximizing expected returns for a given level of risk (Roy 1952). Markowitz (1959) emphasizes semi-variance as a more relevant measure of risk for real-world decision making - focusing primarily on downside risk. When the likelihood of large negative returns is overweighted, investors may undervalue such stocks, reducing demand and resulting in lower prices (Kahneman and Tversky 1979; Barberis and Huang 2008). As prices revert, these stocks may offer higher expected returns. This view is also consistent with evidence that investors extrapolate recent performance into the future (Goetzmann et al. 2016), leading them to avoid stocks that have recently lost value. Investors may, therefore, require a premium for holding stocks that have recently experienced extreme daily losses. Additionally, extreme losses are highly salient and may influence perceived riskiness relative to the other stocks, creating scope for a risk premium (Bordalo et al. 2012; Cosemans and Frehen 2021; Cakici and Zaremba 2022).

Alternatively, stocks that experience extreme negative returns may underperform due to behavioral biases and persistent mispricing. A key mechanism is the disposition effect, where investors avoid selling losing stocks due to regret aversion and self-deception (Shefrin and Statman 1985; Barber and Odean 1999; Grinblatt and Han 2005; Frydman and Camerer 2016). The mispricing is further exacerbated by the fact that realized losses are felt more acutely than paper losses, reinforcing a tendency toward overvaluation (Odean 1998; Barberis and Xiong 2009; Barberis et al. 2016).

Rather than demanding a premium for holding these stocks, investors may often hold on to, or even accumulate, positions in anticipation of a rebound, which can artificially inflate prices.

However, as shown by Atilgan et al. (2020), left-tail risk exhibits strong persistence, particularly among stocks with high retail trading activity. When combined with the well-documented underreaction to bad news (Barberis et al. 1998; Daniel et al. 1998; Hong and Stein 1999; Frazzini 2006), this misperception leads to continued underperformance. Retail investors, in particular, may contribute to this dynamic by maintaining overly optimistic expectations of recovery, thereby supporting inflated valuations. Nevertheless, whether retail investors are net buyers or sellers following extreme negative returns remains an open empirical question in behavioral asset pricing. We aim to fill this gap.

Similar to Caglayan et al. (2023) for the U.S., we construct the *MIN* factor using the minimum daily returns within a given month, for all stocks traded in Borsa Istanbul (BIST) between 2005 and 2024, in order to examine the systematic pricing of extreme negative returns. We first perform univariate portfolio analyses where we sort stocks into five different (quintile) portfolios. Consistent with Caglayan et al. (2023), in our experimental setting, the first quintile (*Low* – *MIN*) contains the stocks with the *lowest* daily losses, and the fifth quintile (*High* – *MIN*) includes the stocks with the *largest* daily losses over the previous month.

Unlike Caglayan et al. (2023), however, our results indicate that the systematic overpricing of *High* – *MIN* stocks. We find that the average return premium associated with the zero-cost strategy between *High* – *MIN* and *Low* – *MIN* stocks is statistically significant and economically large, amounting to -1.4% per month. Our results also suggest that the *MIN* discount cannot be explained by standard asset pricing factors and remains robust in multivariate portfolio tests that control for firm characteristics such as size, value, beta, momentum, reversal, illiquidity, and preference for lottery stocks. Across alternative specifications, the monthly return spread between *High* – *MIN* and *Low* – *MIN* portfolios ranges from -2.3% to -7.9% , with the largest discounts observed when controlling for lottery stock preference (*MAX*).

Firm-level cross-sectional and panel regressions confirm the portfolio analyses. Slope estimates again imply a monthly return discount of approximately -1.4% for a stock that moves from the *Low* – *MIN* group to the *High* – *MIN*. The overpricing of *MIN* stocks becomes more pro-

nounced during periods of short-selling restrictions after February 2020, potentially due to limits to arbitrage (Alkan and Guner 2018). While these findings contrast those presented in Caglayan et al. (2023) for the *MIN* factor, they align with the left-tail anomaly, which is shown to be more prominent under limits to arbitrage and across stocks with high retail investor participation (Atilgan et al. 2020).

In this paper, we also employ a novel dataset consisting of daily portfolios of 20,000 Turkish retail investors across 2008 and 2012, in order to examine the retail trading behavior around minimum return days. Our results suggest an increase in the net buy propensity of retail investors on stocks after their minimum return days, which is in line with our previous findings highlighting the *MIN* discount. More importantly, the net buying tendency of retail investors is primarily observed for stocks that face extreme losses (*High-MIN* stocks) and is driven by younger, male, domestic investors with undiversified portfolios (Odean 1999; Goetzmann and Kumar 2008).

The findings of the paper have direct implications for both academic and practical investment strategies. Our main contribution to the existing literature is to answer the question: Do retail investors buy or sell following extreme negative returns? Our results not only document a significant increase in the average net buying propensity of retail investors following extreme losses, but may also suggest a potential demand side mechanism - through investor, stock, and portfolio characteristics - for the left-tail anomaly of Atilgan et al. (2020), which is especially pronounced among stocks with high retail trading activity. This insight helps clarify why left-tail anomalies are particularly prevalent in markets with high retail investor participation.

To the best of our knowledge, this paper is also the first to document the overpricing associated with the “*MIN* effect” and to propose the *MIN* factor as a left-tail anomaly. Accordingly, our findings contribute to the literature on the systematic pricing of tail risk (Ang et al. 2006; Kelly and Jiang 2014; Bali et al. 2014; Van Oordt and Zhou 2016; Chabi-Yo et al. 2018; Atilgan et al. 2020). Unlike other tail risk or salience-based measures (Cakici and Zaremba 2022) proposed in the literature, however, *MIN* is considerably easier to compute, making strategies based on it substantially more accessible to practitioners (Bali et al. 2011; Caglayan et al. 2023).

The exacerbation of the *MIN* discount during periods of short-selling restrictions highlights the importance of market structure and regulatory constraints in explaining asset pricing anomalies. For regulators, our findings suggest that restricting short-selling - even with the goal of stabilizing markets - may unintentionally sustain inefficiencies and distort price discovery.

2 Data

2.1 Firm-level monthly measures

We obtain daily price and trade volume levels for all stocks traded in Borsa Istanbul (BIST) between January 2005 and December 2024, along with firm-specific accounting measures, and the daily market index (BIST100) levels from the BIST Datastore. We exclude all non-equity instruments and all equities that are not traded in the National market.

For each stock s in each month m in year y , we calculate the firm size ($SIZE_{s,m}$) as the natural logarithm of the end-of-year market value for the given stock s in year $y - 1$. Similarly, the book-to-market ($BTM_{s,m}$) ratio is the ratio between the firm's book value of equity in year $y - 1$ and its market value in year $y - 1$ ¹.

We calculate the market risk of a firm s in month m ($BETA_{s,m}$) as the estimate for the slope coefficient of the market model as follows:

$$R_{s,d} = \alpha + \beta R_d^{mkt} + \varepsilon_{s,d} \quad d = \{1, \dots, D_m\}. \quad (1)$$

where D_m represents the number of trading days in month m , $R_{s,d}$ is the daily returns on stock s in day d and R_d^{mkt} is the market index return in day d .

Liquidity is shown to be an important factor in BIST. Specifically, Atilgan et al. (2016) demonstrate that investors in BIST demand a premium for holding illiquid stocks. Similarly, broker

¹BIST only shares the firm-specific accounting measures at yearly frequency prior to January 2009. Therefore, *SIZE* and *BTM* vary at a yearly frequency in our baseline analyses. We repeat our analysis, excluding the period between 2005 and 2009, and letting *SIZE* and *BTM* vary at a monthly frequency. Our main findings remain robust to this change.

network connections, which are shown to systematically impact the cross-section of equity returns in BIST, are significantly correlated with overall trading volume (Tiniç et al. 2025). To control for variation in liquidity and trading volume, we first define $TV_{s,d}$ to be the Turkish-Lira-denominated trading volume for stock s in trading day d . We then define (Amihud 2002) illiquidity measure ($ILLIQ_{s,m}$) as follows:

$$ILLIQ_{s,m} = \frac{1}{D_m} \sum_{d=1}^{D_m} \frac{R_{s,d}}{TV_{s,d}} * 100. \quad (2)$$

We also set $VOL_{s,m}$ to be the natural logarithm of the total trading volume for firm s in month m . The return momentum ($MOM_{s,m}$) for firm s in month m is taken as the percentage return over the prior six months. That is,

$$MOM_{s,m} = \frac{P_{s,m-1} - P_{s,m-7}}{P_{s,m-7}} \quad (3)$$

where $P_{s,m}$ is the closing price of stock s at the end of month m . In line with Jegadeesh (1990), we define return reversal for each stock s in month m ($REV_{s,m}$) as the return on the stock s over the prior month.

We also calculate the lottery stock characteristics, which systematically influence stock returns in BIST (Alkan and Guner 2018). In line with Bali et al. (2011), we use $MAX_{s,m}$ as the maximum daily return for firm s in a given month m , as follows:

$$MAX_{s,m} = \max(R_{s,d}), \quad d = \{1, \dots, D_m\}. \quad (4)$$

Similarly, we define $MIN_{s,m}$ as the highest daily losses of stock s in a given month m , following Bali et al. (2011) and Caglayan et al. (2023), that is²:

$$MIN_{s,m} = -\min(R_{s,d}), \quad d = \{1, \dots, D_m\}. \quad (5)$$

²In line with Caglayan et al. (2023), we multiply MIN values by -1 to have the highest MIN quantile to include stocks with the largest negative daily losses over the past month and the first quantile to include the stocks with the lowest daily losses over the past month.

Table 1 provides descriptive statistics and pairwise correlations on firm-level monthly measures. In Panel A, the average monthly return (*RETURN*) is around 1%. The mean for *MIN* and *MAX* is around 5% and 6%, respectively. The sample maximums and minimums for *MIN* and *MAX* are respectively around 20% and -20%, which are the broadest circuit breaker levels for the sample covered. In Panel B, we observe a negative and significant correlation between *MIN* and *RETURN*, which may suggest that stocks that experience large daily losses exhibit poor return performance. *MIN* is also significantly negatively correlated with *SIZE* and positively correlated with *ILLIQ*, as expected, which may suggest that small and illiquid firms are more likely to observe large daily losses. In line with Caglayan et al. (2023), we observe that *MIN* is significantly positively correlated with *MAX*.

Insert Table 1 here

2.2 Institutional background for Borsa Istanbul and short-selling restrictions

Borsa Istanbul (BIST) offers a unique setting to examine the pricing of extreme negative returns. Specifically, BIST introduced several restrictions on short-selling activities throughout our sample period. The primary motivation for these restrictions was to maintain market stability and prevent an excessive decline in asset prices. After the global financial crisis, the Capital Markets Board of Turkey (CMBT) increased collateral ratios for short-sales and credit transactions from 50% to 70% between 2011 and 2012 (Alkan and Guner 2018). Examining the regulatory changes during this period, Alkan and Guner (2018) document that the *MAX* discount increased under short-selling restrictions, highlighting limits to arbitrage as a potential mechanism.

In February 2020, short-selling was completely banned in all equity trading on BIST due to the COVID-19 pandemic³. Figure 2 shows the number of different firms sold short monthly during our sample period and illustrates that the market-wide ban began in February 2020. The data on short-selling is also obtained from the BIST Datastore. Although the initial ban lasted only six months,

³See, for example, the CMBT announcement on February 28th, 2020, from the following [link](#) (in Turkish).

provisions after February 2020 lifted restrictions only on a small subset of stocks, representing about 5% of the total number of stocks traded⁴. Following the devastating Kahramanmaraş earthquake, a market-wide short-selling ban was reintroduced in February 2023. We, therefore, define a short-selling restriction dummy, SSR_m , that takes the value of one after February 2020.

Insert Figure 2 here

2.3 Investor portfolios

The sample containing data on daily retail investor portfolios is obtained from the Central Securities Depository of Turkey (MKK). MKK is responsible for the central custody of capital market instruments, monitoring these instruments, and the associated rights. Investor portfolio data consists of 20,000 retail investors' daily stock and fund holdings at Borsa Istanbul between January 2008 and December 2012. The investors in our portfolio data have been selected through a stratified sampling method by MKK to reflect the whole retail investor base characteristics with respect to portfolio size, age, gender, education, and location.

To answer the question of whether retail investors in BIST buy or sell after a stock has experienced an extreme negative return, we treat the minimum return days of each stock in each month as an event and examine the average changes in retail portfolio holdings. To that end, we define $TRADE_{i,s,d}$, which takes 1 (-1) if investor i purchases (sells) stock s on day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days prior to the minimum daily return date for stock s in month m , and zero otherwise. Similarly, $POST_{s,d}^m$ is a dummy that takes one for five days after the minimum daily return for stock s in month m is observed, and zero otherwise. We account for investor portfolio diversification through $NSTOCKS_{i,d}$, which is the number of stocks in individual i 's portfolio on day d (Goetzmann and Kumar 2008).

⁴See the CMBT announcement on June 30th, 2020, from the following [link](#) (in Turkish). BIST30 stocks correspond to the largest 30 firms in Borsa Istanbul, whereas roughly 600 different stocks are traded in our sample period. Since we examine the pricing of extreme negative returns in the cross-section and whether this pricing differs significantly during periods with short-selling restrictions, we treat the period after February 2020 as one in which investors cannot fully correct mispricings through short-selling. Our main results remain robust when we define SSR_m as one between 2008 and 2011, consistent with Alkan and Guner (2018), and after February 2020.

To control for investor characteristics, we define $GENDER_i$ as an indicator variable equal to one if investor i is male. $AGE_{i,d}$ denotes the age of investor i on day d . We proxy investor experience, albeit imperfectly, with $TENURE_{i,d}$, defined as the number of days elapsed since the account opening date for investor i as of day d . Finally, $FOREIGN_i$ is a dummy variable equal to one if investor i is not domiciled in Turkey.

Table 2 presents descriptive statistics and pairwise correlations for the variables constructed from investor portfolio data. As expected, portfolio positions in a given stock do not change on most days for the average investor, as indicated by a sample mean of zero for $TRADE$. The sample is male-dominated, consistent with the broader retail investor population in Turkey: 77% of the observations are attributed to male investors. The average investor is 42.5 years old. On a typical day, investors hold an average of 12 different stocks in their portfolio, although there is considerable variation - some investors hold only a single stock, while others maintain highly diversified portfolios, with the maximum number of holdings reaching 308. Investor experience, measured by account $TENURE$, averages approximately 1,599 days, indicating that investors in our sample have typically maintained an open account for over six years. Finally, only 1% of the observations in our sample are attributed to $FOREIGN$ investors.

Insert Table 2 here

3 Methodology and Results

3.1 Pricing extreme negative returns

3.1.1 Univariate portfolio analysis

We first perform univariate portfolio analyses to examine the systematic impact of extreme negative returns in BIST. We sort stocks into five different (quintile) portfolios. Consistent with Caglayan et al. (2023), in our experimental setting, the first quintile ($Low - MIN$) contains the stocks with the lowest daily losses, and the fifth quintile ($High - MIN$) includes the stocks with

the largest daily losses over the previous month. Let R^{High} and R^{Low} represent the returns of the $High - MIN$ and $Low - MIN$ quintiles in the subsequent month. We then replicate the portfolio of an investor who has held a long position in the stocks with the highest daily losses and a short position of equal size in stocks with the lowest daily losses over the previous month. We test whether investors obtain a premium for the zero-investment MIN strategy described above. Our first hypothesis is as follows:

Hypothesis 1: *The difference between R^{High} and R^{Low} is zero.*

$$H_0 : R^{High} - R^{Low} = 0$$

$$H_A : R^{High} - R^{Low} \neq 0.$$

We test our first hypothesis using a simple t-test, adjusting standard errors for potential heteroskedasticity and autocorrelation with the Newey-West procedure (Newey and West 1987). Next, we examine the return premium associated with the zero-investment MIN strategy while controlling for key asset pricing factors, including market risk, R^{mkt} , size (SMB), and value (HML) factors from Fama and French (1993), as well as the momentum factor (UMD) from Carhart (1997). Specifically, we estimate the parameters of the following regression:

$$R^{High} - R^{Low} = \alpha + \beta_m R^{mkt} + \beta_s SMB + \beta_h HML + \beta_u UMD + \varepsilon. \quad (6)$$

The estimate for the intercept term, $\hat{\alpha}$, represents the return premium associated with the zero-investment MIN strategy. Therefore, we state our second hypothesis as follows:

Hypothesis 2: *The return premium associated with zero-investment univariate MIN portfolio equals zero.*

$$H_0 : \hat{\alpha} = 0$$

$$H_A : \hat{\alpha} \neq 0.$$

Similar to the first hypothesis, we test Hypothesis 2 with a simple t-test where we adjust for potential heteroskedasticity and autocorrelation with the Newey-West procedure.

There are conflicting theoretical expectations about the sign of the alternative hypothesis. On the one hand, investors can demand a premium for holding stocks that have recently faced extreme daily losses. Specifically, investors tend to overweight the probability of extreme negative returns, which leads them to undervalue stocks that have recently experienced sharp losses. This undervaluation results in lower demand, driving prices down. As a consequence, these stocks may have higher expected returns in the subsequent period, as prices revert to fundamental values (Kahneman and Tversky 1979; Barberis and Huang 2008; Caglayan et al. 2023). The perspective aligns with the idea that investors tend to extrapolate past performance into the future (Goetzmann et al. 2016), causing them to reduce demand for stocks that recently experienced large daily losses. Additionally, investors may assess a stock’s attractiveness based on how its returns compare to those of other stocks in the market. As a stock’s most extreme negative returns are particularly noticeable, they may serve as a risk factor that influences investor behavior, leading to a premium for holding such stocks (Bordalo et al. 2012; Cosemans and Frehen 2021). Recently, the empirical findings of (Caglayan et al. 2023) would support this line of argument and suggest, $H_A : R^{High} - R^{Low} > 0$, and $\hat{\alpha} > 0$.

On the other hand, an alternative perspective argues that stocks experiencing extreme negative returns may *underperform* due to behavioral biases and mispricing. One key explanation is the disposition effect, where investors avoid selling losing stocks due to psychological biases such as regret aversion and self-deception (Shefrin and Statman 1985; Barber and Odean 1999; Frydman and Camerer 2016). Instead of demanding a premium for these losses, investors tend to hold on to, or even buy, such stocks in the hope of a rebound, artificially inflating their prices. This mispricing is further exacerbated by the fact that investors experience losses more acutely when realized rather than on paper, reinforcing a tendency toward a persistent *overvaluation* (Odean 1998; Barberis and Xiong 2009; Barberis et al. 2016).

Additionally, stocks that suffer extreme losses may continue to decline because investors systematically underestimate the persistence of left-tail risk. According to Atilgan et al. (2020), large negative returns tend to persist, but investors mistakenly anticipate mean reversion, believing the worst is behind them. However, because left-tail risk does not dissipate as quickly as expected, losses continue, resulting in future underperformance rather than a recovery. Investors' underreaction to bad news further exacerbates this trend, as shown by models from Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), which predict short-run continuations rather than reversals. Empirical studies confirm that underreaction is particularly strong following negative news (Easterwood and Nutt 1999; Hong et al. 2000; Chan 2003).

As a result, instead of offering a risk premium, stocks with high past negative returns may remain overpriced due to misplaced expectations of recovery. This can lead to continued losses, challenging the notion that extreme downside risk is rewarded with higher returns. Instead, it supports the view that these stocks systematically underperform because of behavioral mispricing and the persistent nature of left-tail risk. Recently, empirical findings of Atilgan et al. (2020) would support this line of argument and suggest, $H_A : R^{High} - R^{Low} < 0$, and $\hat{\alpha} < 0$.

Our results indicate that *High* – *MIN* stocks are systematically *overpriced* in BIST. Table 3 provides the characteristics of quintile portfolios based on *MIN*. First, we observe that *MIN* levels increase monotonically from *Low* – *MIN* to *High* – *MIN* quintiles due to the nature of portfolio construction. The average *MIN* difference between *Low* – *MIN* and *High* – *MIN* stocks is around 7% and statistically significant at a 1% level. On average, *High* – *MIN* stocks have smaller market capitalizations, high book-to-market ratios, and greater market risk. They also exhibit stronger momentum, reversal, and are more illiquid despite having higher average trading volumes.

Insert Table 3 here

While the expected returns do not monotonically decrease as we move from *Low* – *MIN* to *High* – *MIN* stocks, the equally-weighted and value-weighted return differentials between *High* – *MIN* and *Low* – *MIN* quintiles are -1.7% and -1.6%, respectively. Both differences are

statistically significant at a 1% level. On average, the expected returns on the *High* – *MIN* stocks are significantly lower than *Low* – *MIN* stocks, indicating that we reject our first hypothesis in favor of *overpricing High* – *MIN* stocks.

Similarly, we also reject the null hypothesis of our second hypothesis in favor of overpricing. In particular, we document that the return premium proxied by the constant term in the four-factor model presented in equation (6), $\hat{\alpha}$, is significantly lower for *High* – *MIN* stocks than *Low* – *MIN* stocks. In Table 3, we observe that both the equally- and value-weighted return premiums are equal to -1.4% on the difference portfolio. Given that the monthly average return is around 1%, these results indicate that the premium associated with the *MIN* strategy is also economically significant.

To further assess the economic significance of the *MIN* strategy in BIST, in Figure 1, we plot the equally- and value-weighted cumulative returns of *the reverse* MIN strategy, that is, a zero-cost strategy long in *Low* – *MIN* stocks and short in *High* – *MIN* stocks. We observe that the reverse *MIN* strategy provides significant positive returns where the equally- and value-weighted cumulative returns are three times higher than the cumulative returns on the benchmark index (BIST 100), further highlighting the economic significance.

Insert Figure 1 here

3.1.2 Multivariate portfolio analyses

The pairwise correlations presented in Table 1 indicate a significant correlation of *MIN* with other firm-specific factors. Therefore, any impact of *MIN* on the cross-section of expected returns should be controlled for different attributes of stocks. To isolate the effect of extreme negative returns, we control for six different firm-specific characteristics (namely, *SIZE*, *BETA*, *MAX*, *ILLIQ*, *MOM*, and *VOL*), individually within a multivariate portfolio analysis framework. At the end of each month, we first sort stocks into three⁵ portfolios based on the control characteristics.

⁵We reduce the quantile number from five to three to ensure that in a multivariate setting each portfolio contains a sufficient number of stocks.

Next, within each control quantile, we further sort stocks into three groups according to their end-of-month *MIN* values, resulting in 9 different portfolios. Finally, we construct zero-investment portfolios, R_p where $p = (Low, 2, High)$, by taking the difference of *High* – *MIN* stocks, R_p^{High} with *Low* – *MIN* stocks, R_p^{Low} . The zero-investment portfolios allow us to assess the systematic impact of extreme negative returns while controlling for other firm-specific factors one at a time. Accordingly, we write our third hypothesis as follows:

Hypothesis 3: *The difference between R_p^{High} and R_p^{Low} is zero for any p in a multivariate setting.*

$$H_0 : R_p^{High} - R_p^{Low} = 0$$

$$H_A : R_p^{High} - R_p^{Low} < 0.$$

We employ a standard t-test when examining our third hypothesis, where we correct our standard errors for potential heteroskedasticity and autocorrelation using Newey-West standard errors.

We further test the return premium associated with our multivariate zero-investment portfolios R_p , controlling for *SMB*, *HML*, and *UMD* as follows:

$$R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p \quad p = \{1, 2, 3\}. \quad (7)$$

We then test the hypothesis that the constant terms $\hat{\alpha} \equiv \{\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3\}$, are jointly equal to zero. Our fourth hypothesis is given below:

Hypothesis 4: *The return premiums associated with zero-investment multivariate MIN portfolios are jointly equal to zero.*

$$H_0 : \hat{\alpha} = 0$$

$$H_A : \hat{\alpha} < 0.$$

We employ the Gibbons-Ross-Shanken (GRS) test statistic of Gibbons et al. (1989) to test Hypothesis 4. Since we established that the *MIN* factor results in the overpricing of stocks in the cross-section, we expect this relationship to continue in the multivariate setting and, hence, expect R_p and $\hat{\alpha}$ to be, on average, negative.

Similar to the results of our univariate tests, we observe that stocks with extreme negative returns are associated with future negative returns even after accounting for control factors, suggesting overpricing. Table 4 provides the results for our third hypothesis. Table 4 looks crowded but very easy to follow.

Insert Table 4 here

Each panel (Panels A to F), respectively, provides the portfolio characteristics where the control is *SIZE*, *BETA*, *MAX*, *ILLIQ*, *MOM*, and *VOL*. In all corresponding panels, the first subpanel denotes the average *MIN* values of each portfolio specification. The second subpanel provides the average values for the control variable, that is, for example, Panel A2 (B2) [C2], the *SIZE*, (*BETA*) [*MAX*] values of each *SIZE* – *MIN*, (*BETA* – *MIN*), and [*MAX* – *MIN*] portfolios. As expected, we observe that stocks with high market capitalization, on average, have lower extreme negative returns. *High* – *BETA* stocks are generally associated with higher extreme negative returns. In line with Caglayan et al. (2023), stocks with high extreme negative and high extreme positive returns move together on average. Aside from the first *MIN* quantile, illiquid stocks tend to have higher extreme negative returns. On the contrary, the extreme returns seem higher on average for stocks with high trade volume.

The third panel presents the expected returns associated with zero-investment *MIN* portfolios for the corresponding control variable. In Panels A3 and B3, the variations in *SIZE* and *BETA* do not help explain away the *MIN* discount. The returns associated with zero-cost *MIN* portfolios vary between -2.4% and -4%, all statistically significant at a 1% level. In Caglayan et al. (2023), the overlap between *MIN* and *MAX* stocks is shown to obscure the pricing of extreme negative

returns. After excluding *High* – *MAX* stocks, the *MIN* impact becomes significant, pointing to a possible role for lottery-like stocks in masking the *MIN* effect (Bali et al. 2011). *MAX* factor is also prominent in BIST (Alkan and Guner, 2018). However, our results suggest that *MAX* cannot properly explain the impact of *MIN*, as the expected returns on zero-cost *MAX* – *MIN* portfolios are negative and statistically significant in Panel C3. The economic significance of the *MIN* factor seems to increase after controlling for the lottery stock characteristics, as the size of the expected return on the zero-cost portfolios varies between -7% and -8%, the largest among all multivariate portfolio specifications. The pricing of the *MIN* factor also stays significant after controlling for liquidity (*ILLIQ*), which is another important pricing factor in BIST (Atilgan et al. 2016). Similarly, Table 3 shows that *MOM*, *REV*, and *VOL* do not impact the *MIN* factor’s statistical and economic significance. In Panels D3, E3, and F3, the expected returns on all zero-cost portfolios remain statistically and economically significant.

Next, we examine the return premiums associated with multivariate zero-cost portfolios and present the results of tests for our fourth hypothesis in Table 5. Similar to Table 4, Panels A through F display portfolios constructed on *SIZE*, *BETA*, *MAX*, *ILLIQ*, *MOM*, and *VOL* as control variables, respectively. In Panel A, all zero-cost *SIZE* – *MIN* portfolios reflect a significant discount, with alphas ranging from -2.6% to -4.2%. The GRS test rejects the null hypothesis that the constant terms are jointly equal to zero, underscoring the systematic overpricing of *MIN* stocks in BIST even after controlling for firm size. In Panel B, the pricing of the *MIN* factor remains robust after controlling for *BETA*, with alphas between -2.9% and -3.5%, all statistically significant, and a similarly significant GRS test result. Panel C shows that *MAX* – *MIN* portfolios exhibit the largest economic significance for the *MIN* discount, with alphas between -6.8% and -7.9%, and the GRS test again rejects the null of Hypothesis 4 – unlike the results in Caglayan et al. (2023), who address the overlap between *MIN* and *MAX* by excluding *High* – *MAX* stocks rather than testing whether *MIN* remains significant when controlling for *MAX* directly. In Panel D, controlling for liquidity, we find alphas between -2.8% and -4.3%, all statistically significant, with a GRS test rejecting the joint null. Panel E shows that *MIN* continues to exhibit a significant

discount after controlling for return momentum with alphas from -2.3% to -6.2%. Finally, Panel F indicates that controlling for volatility also leaves a significant MIN discount with alphas ranging around 4% and a significant GRS test statistic, rejecting the null hypothesis that return premiums are jointly equal to zero. Overall, these results consistently support the argument that *MIN* stocks are systematically overpriced, controlling across different firm characteristics⁶.

Insert Table 5 here

3.1.3 Firm level cross-sectional and panel regressions

One limitation of the multivariate portfolio analysis is that it allows us to control for only one firm-specific characteristic at a time. We complement our analysis with firm-level cross-sectional regressions (akin to Fama and MacBeth (1973)) to address this constraint and simultaneously account for multiple characteristics. Specifically, for each month in our sample, we regress future stock returns on *MIN* factor, including all relevant firm-specific control variables in the specification:

$$RETURN_{s,m+1} = \gamma_{0,m} + \gamma_{1,m}MIN_{s,m} + \sum_{k=2}^9 \gamma'_{k,m} X_{s,m}^k + \varepsilon_{s,m}. \quad (8)$$

where $RETURN_{s,m+1}$ is the monthly return on stock s in month $m + 1$. $MIN_{s,m}$ is the minimum daily return for stock s in month m . The matrix $X_{s,m}$ includes all firm-specific controls, *SIZE*, *BETA*, *BTM*, *MOM*, *REV*, *MAX*, *ILLIQ*, and *VOL*. Our fifth hypothesis is then given as follows:

Hypothesis 5: *There is no significant predictive relationship between MIN and future returns.*

$$H_0 : \overline{\gamma_1} = 0$$

$$H_A : \overline{\gamma_1} < 0.$$

⁶Appendix provides the portfolio characteristics and results for the factor regressions for *IVOL* – *MIN* portfolios where *IVOL* is defined as the standard deviation of residuals obtained from equation (1). The results suggest that *MIN* is systematically priced in BIST even after controlling for firm-specific variations in idiosyncratic risk *IVOL*.

We expect a negative relationship between MIN and future returns to be consistent with our previous results documenting the overpricing of MIN stocks. When testing our fifth hypothesis, we employ Newey-West standard errors for potential heteroskedasticity and autocorrelation.

Table 6 reports the results of firm-level cross-sectional regressions. The coefficient of interest, $\overline{\gamma}_1$, is negative and statistically significant in all specifications, consistent with earlier evidence of overpricing in MIN stocks. In column (1), the slope estimate for univariate regression is -0.307. The economic magnitude of the MIN discount, therefore, aligns with previous results. For instance, Table 3 shows that the average MIN difference between $Low - MIN$ and $High - MIN$ stocks is 0.066. Multiplying this by the estimated slope implies a MIN discount of approximately 2% when moving from the $Low - MIN$ to the $High - MIN$ portfolio. The coefficient for MIN for the most extended model in column (9) is -0.209, indicating a discount of around -1.4%, which is equivalent to the difference we observed in Table 3⁷.

Insert Table 6 here

Petersen (2008) indicates that the standard errors in firm-level cross-sectional regressions can be underestimated if there is clustering. Therefore, next, we estimate the predictive relationship between MIN and future returns in a panel regression setting with firm and time (month-year) fixed effects, as presented below:

$$RETURN_{s,m+1} = \theta_s + \nu_m + \gamma_1 MIN_{s,m} + \sum_{k=2}^9 \gamma'_k X_{s,m}^k + \varepsilon_{s,m}. \quad (9)$$

where θ_s and ν_m , respectively, correspond to firm- and time-fixed effects. Similar to Hypothesis 5, we write our sixth hypothesis as follows:

Hypothesis 6: *There is no significant predictive relationship between MIN and future returns.*

$$H_0 : \hat{\gamma}_1 = 0$$

⁷The predictive relationship between MIN and future returns remains to be statistically and economically significant when we employ $RETURN_{s,m+12}$ as a dependent variable in equation (8), highlighting a long-term impact.

$$H_A : \hat{\gamma}_1 < 0$$

When testing our sixth hypothesis, we cluster standard errors with respect to firm and time (month-year). Table 7 presents the panel regression results. The results remain consistent with our previous findings. We observe that the coefficient for MIN , $\hat{\gamma}_1$ remains negative and statistically significant in all specifications. The coefficient varies between -0.321 and -0.156, indicating an economically significant MIN discount. Specifically, we can argue that moving from the *Low* – MIN quantile to the *High* – MIN quantile would result in a 1% to 2% average reduction in future expected returns⁸.

Insert Table 7 here

3.2 Short-selling restrictions and the pricing of extreme negative returns

The results presented thus far consistently show that stocks experiencing extreme negative daily returns tend to deliver lower future returns in the Borsa Istanbul. In univariate and multivariate portfolio analyses, we document a significant and economically meaningful return discount for stocks in the highest MIN quantiles compared to those within the lowest MIN quantile. Similarly, our firm-level cross-sectional and panel regressions confirm that the MIN factor is strongly negatively related to future returns, even when accounting for multiple firm-specific attributes simultaneously.

Taken together, this evidence suggests that investors do not receive a premium for bearing extreme downside risk. Rather, the findings imply that stocks that experience large daily losses are systematically overpriced, resulting in predictable underperformance. Arbitrageurs, in principle, should correct overvaluation by aligning prices with fundamental values through short selling. However, arbitrage in secondary markets is risky and constrained by capital limitations, which can

⁸The predictive relationship between MIN and future returns remains to be statistically and economically significant when we employ $RETURN_{s,m+12}$ as a dependent variable in equation (9), further highlighting a long-term impact.

impede the full correction of mispricing (Shleifer and Vishny 1997; Pontiff 2006). Consistent with the limits to arbitrage mechanism, Stambaugh et al. (2015) and Cao and Han (2016) document that the magnitude of several return anomalies depends systematically on limits-to-arbitrage, with overpriced stocks remaining mispriced longer when these frictions are high. Extending this idea, Atilgan et al. (2020) argue that when arbitrage is costly, rational investors are less able to trade against underreaction to bad news, resulting in persistent left-tail momentum.

Therefore, we next examine whether the impact of the *MIN* factor is exacerbated under short-selling restrictions in BIST. Short-selling restrictions provide an important setting to understand how the pricing of stocks that experience extreme negative returns may change when investors are constrained in their ability to arbitrage away mispricing. The relevance of this mechanism is also supported by prior evidence for BIST. Alkan and Guner (2018) show that the discount for stocks with lottery-like payoffs becomes more pronounced during periods of short-selling restrictions. While their focus is on extreme positive returns, a similar friction likely affects *MIN* stocks if investors hold or buy them in anticipation of a reversal. Without the possibility to short, pessimistic investors may be forced to exit or abstain from trading altogether, leaving prices artificially elevated. To test this prediction, we extend equation (9) to include $SSR_{s,m}$ along with the corresponding interaction terms, specifying the panel regression as follows:

$$\begin{aligned} RETURN_{s,m+1} = & \theta_s + \nu_m + \gamma_1 MIN_{s,m} + \delta_1 (MIN_{s,m} \times SSR_m) \\ & + \sum_{k=2}^9 [\gamma_k X_{s,m}^k + \delta_k (X_{s,m}^k \times SSR_m)] + \varepsilon_{s,m}. \end{aligned} \quad (10)$$

where SSR_m is a dummy that takes one after February 2020. The matrix $X_{s,m}$ includes all firm-specific controls, *SIZE*, *BETA*, *BTM*, *MOM*, *REV*, *MAX*, *ILLIQ*, and *VOL*. θ_s and ν_m , respectively, correspond to firm- and time-fixed effects. Our seventh hypothesis is as follows:

Hypothesis 7: *There is no significant change in MIN discount during periods of short-selling*

restrictions.

$$H_0 : \hat{\delta}_1 = 0$$

$$H_A : \hat{\delta}_1 < 0$$

A negative and statistically significant estimate of δ_1 would indicate that the return discount associated with extreme negative returns is more pronounced when short-selling restrictions are binding, consistent with the limits-to-arbitrage mechanism. Table 8 presents the results. In all specifications, the coefficient for *MIN* remains negative and statistically significant at a 1% level. This confirms that stocks experiencing extreme negative daily returns tend to underperform, consistent with our previous results.

Insert Table 8 here

More importantly, the interaction term $MIN \times SSR (\hat{\delta}_1)$ is negative and statistically significant across all specifications using OLS standard errors in Panel A. When standard errors are clustered across firms and time, the interaction term remains negative and statistically significant in columns (1) and (2) but becomes insignificant in column (3), where we include firm-fixed effects along with firm-specific controls. The decline in significance under clustered standard errors suggests that the amplified effect of short-selling restrictions is sensitive to the inclusion of firm fixed effects and additional controls.

While the insignificance in the final specification warrants caution, the overall pattern still provides suggestive evidence that short-selling constraints can exacerbate the overpricing of extreme negative returns. This is consistent with the broader limits-to-arbitrage mechanisms highlighted by Alkan and Guner (2018) for stocks with lottery-like payoffs and extends the logic to downside risk.

In terms of economic magnitude, the estimates imply that, conditional on binding short-selling restrictions, a one percentage point increase in *MIN* is associated with an *additional* decrease in future returns of approximately 10-20 basis points per month in specifications where the effect is

significant. Given the low average monthly return level in BIST, this represents an economically significant impact.

Overall, the results in Table 8 provide partial support for the hypothesis that the mispricing of stocks with extreme negative returns is more severe when pessimistic beliefs cannot be fully acted upon due to limits on short selling.

4 Do retail investors buy or sell after extreme negative returns?

So far, our results suggest that stocks that face extreme negative returns are systematically overpriced in Borsa Istanbul (BIST). The mispricing seems to exacerbate under short-selling restrictions, potentially due to limits to arbitrage. A possible explanation for the underperformance of stocks with extreme negative returns emphasizes behavioral biases that give rise to persistent overpricing. A central mechanism is the investors' reluctance to realize losses due to regret aversion and self-deception, leading them to hold or even accumulate losing stocks in anticipation of a rebound (Shefrin and Statman 1985; Barber and Odean 1999; Frydman and Camerer 2016). This behavior suppresses selling pressure and supports inflated valuations, particularly because losses are felt more acutely when realized rather than on paper (Odean 1998; Barberis and Xiong 2009; Barberis et al. 2016).

Moreover, the persistence of negative returns is often underestimated. Investors tend to anticipate mean revision after large losses, expecting the worst to be over. However, as shown by Atilgan et al. (2020), left-tail risk is highly persistent, and when combined with investors' underreaction to bad news (Barberis et al. 1998; Daniel et al. 1998; Hong and Stein 1999), this misperception leads to continued underperformance. Atilgan et al. (2020) also show that persistence of left-tail risk is significantly more apparent on stocks with high retail trading activity. Thus, stocks with large prior losses may remain overpriced due to misplaced optimism of retail investors, even though whether retail investors buy or sell stocks that face extreme negative returns remains an open

question.

In this section, we employ a daily sample on portfolios of retail investors in BIST and examine the average response of retail investors to minimum return days, contributing to the ongoing debate. The baseline setup is as follows:

$$TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}. \quad (11)$$

where $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. Similarly, $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. Our coefficient of interest is, therefore, β_3 . α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects.

If retail investors contribute to the persistence and overvaluation of stocks experiencing extreme negative returns - whether due to expectations of mean reversion or behavioral biases such as the disposition effect - then we expect them, on average, to be net buyers following the minimum return day. Our eighth hypothesis is, therefore, given as follows:

Hypothesis 8: *There is no significant change in retail investor portfolios after a minimum return day.*

$$H_0 : \hat{\beta}_3 = 0$$

$$H_A : \hat{\beta}_3 > 0$$

We cluster standard errors with respect to investors and stocks when testing Hypothesis 8. The results are presented in Table 9. Columns (1) and (2) report specifications of equation (11) that exclude the days prior to the minimum return day (PRE). Figure 3 graphically illustrates the coefficient estimates from column (4) of Table 9. We clearly reject Hypothesis 8. Specifically, we observe that the net buying propensity of retail investors, on average, increases by 8 to 11 basis

points (bps) on the minimum return day. In the days following the minimum return, the average increase in net buying is around 60 bps, which is both statistically and economically significant. These findings suggest that retail investors, on average, act as net buyers on and after minimum return days. This behavior is consistent with the conjecture that retail trading activity contributes to the persistence and overvaluation of stocks experiencing negative returns (Atilgan et al. 2020). The negative and significant coefficient on *PRE* in columns (3) and (4) of Table 9 may suggest anticipatory selling, possibly due to worsening news or left-tail momentum leading into the trough.

Insert Table 9 here

Insert Figure 3 here

We then investigate whether trading behavior surrounding a minimum return day varies by investor characteristics, starting with gender and domicile, as well as age, account tenure, and portfolio diversification.

We begin by splitting the sample based on *GENDER* and estimating the equation (11) separately for male and female investors. Table 10 reports the resulting coefficient estimates, as well as the estimates for the interaction terms. We also represent the results in Columns (1) and (2) in Figure 4, which show that male investors exhibit a net buy tendency of 62 bps following the minimum return day, compared to 41 bps for female investors. The 21 bps difference is both economically and statistically significant, as confirmed by the significance of the interaction term reported in Column (3).

Insert Table 10 here

Insert Figure 4 here

A similar gender-based difference is evident on the day of the minimum return event (*DAY0*). Male investors show a statistically significant net buy tendency of approximately 105 bps at the 5% level. In contrast, while female investors display a positive coefficient on *DAY0*, the effect is not statistically significant. The gap in net buy tendency between male and female investors on the minimum return day amounts roughly to 95 bps and is statistically significant at a 1% level.

Overall, these results suggest that female investors tend to be more conservative in their trading behavior around minimum return days. This interpretation is further supported by the finding that, while both male and female investors exhibit negative coefficients on PRE , the interaction term $PRE \times GENDER$ is negative and statistically significant. This implies that, on average, male investors show a significantly stronger tendency to sell prior to, and to buy on and after, minimum return days.

It is important to note, however, that the economic significance of the gender difference in the days leading up to the minimum return day is relatively modest - around 7bps. This suggests that the main divergence in average trading behavior across genders emerges after the minimum return day, rather than before.

Next, we divide our sample based on $FOREIGN$ and estimate the coefficients from equation (11) separately for domestic and foreign investors. Table 11 presents the regression results for each subsample along with estimates from a pooled model that includes interaction terms. Figure 5 also graphically demonstrates the estimates from each subsample.

Insert Table 11 here

Insert Figure 5 here

In the five days following a minimum return day ($POST$), domestic investors display a strong net buy tendency of approximately 57 bps, while foreign investors increase their holdings by only 30 bps. This difference is statistically significant at a 1% level, as captured by the negative and significant interaction term $POST \times FOREIGN$. This result suggests that domestic investors are substantially more aggressive in purchasing stocks after large price declines.

Although the economic magnitude of the divergence is even larger on the day of the minimum return ($DAY0$), the interaction term is not statistically significant, indicating that the differential behavior is more prominent in the post-event period. Similarly, we do not find significant differences between foreign and domestic investors in anticipatory selling behavior prior to the minimum return day. These findings are consistent with the results reported in Table 10, which

suggest that the divergence in investor behavior emerges primarily after the occurrence of extreme negative returns.

Table 12 presents an expanded analysis of investor heterogeneity in response to minimum return days, focusing on how trading behavior varies across observable investor characteristics. Columns (1) and (2) of Table 12 replicate the interaction specifications from Column (3) of Tables 10 and 11, respectively, providing reference points for gender- and domicile-based differences. In Columns (3) through (6) of Table 12, we explore additional sources of heterogeneity by interacting *POST*, *DAY0*, and *PRE* with investor characteristics such as investor age, account tenure, and portfolio diversification (measured by the number of distinct stocks held, *NSTOCKS*, (Goetzmann and Kumar 2008)). Whereas earlier tables isolate a single source of heterogeneity at a time, Column (6) offers a more comprehensive specification by jointly incorporating multiple interaction terms, which enable direct comparison across dimensions in a unified framework.

Insert Table 12 here

Our results highlight a positive and significant coefficient for *POST* across all alternative specifications in Table 12. This finding suggests that the net buy tendency of retail investors after a minimum return day is robust even after controlling for observables with respect to investors, accounts, and portfolios, along with unobserved heterogeneity across investors, stocks, and time.

In addition, we observe a negative and statistically significant interaction between *POST* and $\log(AGE)$ in Column (3), with a coefficient of approximately -25 bps, indicating that younger investors are more inclined to buy after sharp price declines. While the $POST \times \log(TENURE)$ and $POST \times \log(NSTOCKS)$ interactions are not statistically significant in Columns (4) - (6), we *do* find notable heterogeneity in trading on the minimum return day (*DAY0*). Specifically, $DAY0 \times \log(AGE)$ and $DAY0 \times \log(NSTOCKS)$ both yield negative and statistically significant coefficients in Columns (3) and (5), implying that younger and less diversified (concentrated) investors are more likely to buy on the minimum return day. The average net buy tendency on *DAY0* is further confirmed by the consistent positive coefficients across all columns, albeit statistically insignificant in Column (2).

On the anticipatory trading side, the baseline coefficient for PRE is negative and significant across all specifications except in Column (4). PRE interactions further support heterogeneity on the days prior to the minimum return day. We observe that older and more diversified investors are less likely to sell prior to a minimum return day, as indicated by the positive $PRE \times \log(AGE)$ and negative $PRE \times \log(NSTOCKS)$ coefficients in Columns (3) and (5), both statistically significant at the 1% and 5% levels, respectively.

Taken together, the results in Table 12 underscore a systematic pattern in how retail investors respond to minimum return days. Younger, male, domestic, and less diversified investors consistently exhibit a stronger buy tendency either on or shortly after the minimum return day. This heterogeneity across investors may contribute to the persistence of mispricing, especially in stocks with high retail trading activity.

What happens to retail investor behavior as the downside returns on minimum return days become extreme? To answer this question, we employ the monthly classifications used in the univariate portfolio analysis at the stock level and divide stocks into *High-MIN* and *Low-MIN* quintiles based on the magnitude of their minimum return. We then incorporate these groupings into the baseline specification in equation (11) by interacting them with PRE , $DAY0$, and $POST$ to examine whether trading behavior differs with the intensity of the downturn. Table 13 presents the regression results. Column (1) includes interactions of *High-MIN* with $DAY0$ and $POST$ only. Column (2) extends this by introducing both *High-MIN* and *Low-MIN* interactions with $DAY0$ and $POST$. Column (3) returns to a focus on *High-MIN* but incorporates all three periods: PRE , $DAY0$, and $POST$. Finally, Column (4) provides the most comprehensive specification, in which both *High-MIN* and *Low-MIN* interactions are included for all three windows. Figure 6 provides a graphical representation of the coefficient estimates reported in Column (4).

Insert Table 13 here

Insert Figure 6 here

In Table 13, we first observe positive (negative) and statistically significant baseline estimates

for $High - MIN$ and $Low - MIN$ stocks, which indicate that, on average, investors increase (decrease) their net buy tendency for such stocks, irrespective of the minimum return day, throughout our sample period. The estimate for $POST$ is statistically significant at a 1% level in all alternative specifications, indicating that the net buy tendency of retail investors is robust to the control for the intensity of the downside return. The estimates vary between 42 and 48 bps, depending on the specification, significantly lower than those presented in Table 9.

Importantly, we observe a positive and significant estimate for the interaction term $POST \times (High - MIN)$, whereas the estimate for the interaction term $POST \times (Low - MIN)$ is significantly negative across all alternative specifications. For $POST \times (High - MIN)$, the coefficient estimates differ between 85 and 90 bps, almost doubling the baseline for $POST$. The results indicate that retail investors exhibit substantially stronger net buy propensity responses when the loss is more extreme. In contrast, for $Low - MIN$ stocks, the economic significance of the net buy propensity largely disappears after the minimum return day.

In Table 13, we further observe that the net buy propensity of retail investors largely disappears after accounting for the intensity of the downside return on the minimum return day. Even though the baseline estimate for DAY is positive in all alternative specifications, it loses statistical significance in the most comprehensive specification presented in Column (4). Interestingly, we observe a negative coefficient estimate for $DAY0 \times (High - MIN)$ across all specifications, but it is statistically insignificant in specifications where we exclude PRE from the model. Similarly, we observe negative but insignificant estimates for $DAY0 \times (Low - MIN)$, indicating that the intensity of the minimum return has no additional impact on retail trading behavior on the minimum return day.

Finally, the baseline average anticipatory selling prior to minimum return days presented in Table 9 is further confirmed in Table 13. PRE has negative and significant coefficient estimates across all specifications. The coefficients are around -15bps in line with the baseline estimates. We further observe a statistically and economically significant coefficient for the interaction term $PRE \times (High - MIN)$, around -16 bps. However, the coefficient for the interaction term $PRE \times$

($Low - MIN$) is insignificant. These findings may suggest that, similar to those presented for $POST$, the anticipatory selling activity prior to minimum return days is primarily driven by stocks that experience extreme negative returns.

To sum up, in this section, we present the retail investors' average net buy tendency on and after the minimum return days. This is consistent with the literature and in line with our previous findings suggesting overpricing on the MIN factor. We further document that young, male, domestic investors with concentrated portfolios are the primary drivers of the average net buy tendency on and after minimum return days. Finally, we underline that the net buy tendency after the minimum return days is mainly observed for stocks that face extreme negative returns, contributing to the mispricing. In this context, our findings offer a potential mechanism for the left-tail risk anomaly primarily observed for stocks with high retail trading activity (Atilgan et al. 2020), by highlighting how heterogeneity across investors, portfolios, and stocks can reinforce return patterns associated with downside risk.

5 Conclusion

This paper examines the systematic pricing of extreme negative returns in equity markets and the retail investor behavior around minimum return days. There are conflicting theoretical predictions regarding how stocks with large daily losses should be priced. On one hand, such losses may be perceived as a salient risk factor, prompting investors to demand a premium to hold these stocks. If investors overweigh the probability of another sharp decline or extrapolate past performance into the future, demand may drop and prices may fall, implying higher future expected returns. On the other hand, behavioral forces such as the disposition effect and underreaction to bad news may instead lead to persistent overvaluation. Investors may also hold or accumulate losing stocks in anticipation of a rebound or to avoid realizing their losses, inflating prices despite continued exposure to downside risk. In this case, stocks with extreme past losses would earn lower future returns.

We test these competing views and sort stocks based on the minimum daily returns for each

month (MIN). The univariate portfolio analysis reveals that stocks in the highest MIN quintile, those with the most extreme daily losses, earn significantly lower returns than those in the lowest MIN quintile, indicating overpricing. The average return premium associated with the zero-cost difference strategy between $High - MIN$ and $Low - MIN$ stocks is statistically significant and amounts to -1.4% per month, suggesting that the overpricing is also economically significant and cannot be explained by standard asset pricing factors.

The discount remains robust in multivariate portfolio tests that control for key firm characteristics. Across different specifications, the return premium on $High-Low$ portfolios ranges from -2.3% to -7.9% per month, with the largest discounts observed when controlling for extreme positive returns MAX . GRS tests consistently reject the joint null that these return premiums are zero.

Firm-level cross-sectional and panel regressions confirm the pattern, with the slope estimates implying return differences, again, around -1.4% between $High - MIN$ and $Low - MIN$ stocks. Overall, the results point to significant overpricing of MIN , which becomes more pronounced during periods of short-selling restrictions after February 2020, possibly because of limits to arbitrage.

Finally, using daily portfolio changes of 20,000 retail investors in BIST, we document that Turkish retail investors, on average, increase their stock holdings following minimum return days. The increase in propensity to buy around the minimum return day is significantly higher for young, male, domestic investors with concentrated portfolios. More importantly, we highlight that the net buy tendency around the minimum return day is primarily observed for stocks with the most extreme negative returns ($High - MIN$ stocks).

Overall, our findings suggest “ MIN effect” as a left-tail risk anomaly which is primarily observed for stocks with high retail trading activity. The MIN discount is heightened during periods with short-selling restrictions, implying for regulators that the rules put in place to stabilize the markets may unintentionally result in exacerbated inefficiencies. This finding underscores how limits to arbitrage interact with investor behavior to entrench anomalies in real-world markets,

especially in emerging economies like Turkey.

We, therefore, offer a potential mechanism for left-tail risk anomaly by underlining how heterogeneity across retail investors, portfolios, and stocks can reinforce mispricing. These insights help clarify why left-tail anomalies are particularly pronounced in markets with high retail investor participation and limited institutional arbitrage.

Tables and Figures

Panel A: Descriptive Statistics											
Variable	RETURN	MIN	BETA	SIZE	BTM	MOM	REV	ILLIQ	MAX	VOL	SSR
Observations	93,722	94,498	94,466	79,095	76,701	89,117	92,948	94,498	94,498	94,498	94,498
Mean	0.01	0.05	0.64	19.73	0.87	0.18	0.01	0.01	0.06	18.32	0.28
Std. Dev.	0.19	0.03	0.65	2.25	1.21	0.91	0.19	0.14	0.04	3.45	0.45
Minimum	-4.38	-0.18	-35.98	13.65	0.00	-1.00	-4.38	0.00	-0.11	0.02	0.00
Maximum	2.08	0.20	18.75	27.13	61.42	164.58	2.08	16.41	0.20	35.72	1.00

Panel B: Pairwise Correlations											
RETURN	1										
MIN	-0.222***	1									
BETA	-0.0993***	0.213***	1								
SIZE	0.0800***	-0.0571***	0.170***	1							
BTM	-0.129***	0.0133***	-0.0184***	-0.293***	1						
MOM	-0.0314***	0.148***	0.0036	0.118***	-0.142***	1					
REV	0.0300***	0.0634***	-0.0244***	0.0811***	-0.134***	0.289***	1				
ILLIQ	-0.0045	0.0181***	-0.0284***	-0.0600***	0.00982**	-0.00770*	-0.00284	1			
MAX	0.260***	0.459***	0.0748***	-0.0607***	-0.0417***	0.118***	0.0568***	0.00914**	1		
VOL	0.0653***	0.0480***	0.165***	0.766***	-0.238***	0.106***	0.0710***	-0.0852***	0.104***	1	
SSR	0.0579***	0.150***	0.0849***	0.500***	-0.232***	0.163***	0.0527***	-0.0217***	0.121***	0.369***	1

Table 1: **Descriptive statistics of firm-specific measures** - This table presents the descriptive statistics and pairwise correlations of firm-specific variables calculated for all stocks traded in Borsa Istanbul between 2005 and 2024. *RETURN* is the monthly logarithmic returns. *MIN* is the minimum daily return multiplied by -1. *BETA* is the systematic risk factor captured by the slope coefficient of the market model. *SIZE* is the logarithm of the end-of-year market capitalization. *BTM* is the book-to-market ratio. *MOM* represents the return momentum. *REV* is the return reversal captured by the one-month lag return. *ILLIQ* is the Amihud illiquidity measure (Amihud 2002). *MAX* is the maximum daily return within a month. *VOL* is the logarithm of the Turkish Lira-denominated trade volume. *SSR* is a dummy capturing short-selling restrictions in BIST, taking the value one after February 2020, and zero otherwise. Panel A presents the number of observations, mean, standard deviation, minimum, and maximum values for each variable. Panel B presents the pairwise correlations. ***, **, * indicates statistical significance at a 1%, 5%, and 10% level, respectively.

Panel A: Descriptive Statistics

	TRADE	PRE	DAY0	POST	GENDER	AGE	TENURE	NSTOCKS	FOREIGN
Observations	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695
Mean	0.00	0.18	0.03	0.17	0.77	42.57	1599.78	11.80	0.01
Std. Dev.	0.14	0.38	0.18	0.38	0.42	7.81	545.81	22.16	0.09
Minimum	-1.00	0.00	0.00	0.00	0.00	18.00	2.00	1.00	0.00
Maximum	1.00	1.00	1.00	1.00	1.00	59.00	2593.00	308.00	1.00

Panel B: Pairwise correlations

	1								
TRADE	1								
PRE	-0.00604***	1							
DAY0	0.000291**	-0.0652***	1						
POST	0.0166***	-0.133***	-0.0664***	1					
GENDER	0.00493***	0.00661***	-0.000219*	0.00548***	1				
AGE	-0.00400***	-0.00945***	0.000112	-0.00788***	-0.0245***	1			
TENURE	-0.00429***	0.00871***	-0.000413***	-0.0154***	0.0142***	0.0515***	1		
NSTOCKS	-0.000404***	-0.00647***	0.000186	-0.00585***	0.0403***	0.00584***	0.0241***	1	
FOREIGN	-0.00129***	-0.00143***	0.00000675	-0.00118***	-0.0499***	0.0148***	0.00782***	0.0329***	1

Table 2: **Descriptive statistics for retail investor portfolios** - This table presents the descriptive statistics and pairwise correlations for the investor portfolio sample. The sample containing data on daily retail investor portfolios is obtained from the Central Securities Depository of Turkey (MKK). The investor portfolio sample consists of 20,000 retail investors' daily stock and fund holdings at Borsa Istanbul between January 2008 and December 2012. The investors in our portfolio data have been selected through a stratified sampling method by MKK to reflect the whole retail investor base characteristics with respect to portfolio size, age, gender, education, and location. $TRADE_{i,s,d}$, which takes 1 (-1) if investor i purchases (sells) stock s on day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days prior to the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days after the minimum daily return for stock s in month m is observed, and zero otherwise. $NSTOCKS_{i,d}$, which is the number of stocks in individual i 's portfolio on day d . $GENDER_i$ is an indicator variable equal to one if investor i is male. $AGE_{i,d}$ denotes the age of investor i on day d . We proxy investor experience, albeit imperfectly, with account $TENURE_{i,d}$, defined as the number of days elapsed since the account opening date for investor i as of day d . $FOREIGN_i$ is a dummy variable equal to one if investor i is not domiciled in Turkey. Panel A presents the number of observations, mean, standard deviation, minimum, and maximum values for each variable. Panel B presents the pairwise correlations. ***, **, * indicates statistical significance at a 1%, 5%, and 10% level, respectively.

	<i>Low</i> – <i>MIN</i>	2	3	4	<i>High</i> – <i>MIN</i>	<i>High</i> – <i>Low</i>	<i>se</i> (<i>High</i> – <i>Low</i>)	<i>t</i> (<i>High</i> – <i>Low</i>)	<i>p</i> (<i>High</i> – <i>Low</i>)
α -EW	-0.003	-0.008	-0.009	-0.008	-0.018	-0.014***	(0.00)	(-5.13)	(0.00)
α -VW	-0.004	-0.008	-0.010	-0.008	-0.018	-0.014***	(0.00)	(-5.07)	(0.00)
<i>RETURN</i> – <i>EW</i>	0.010	0.007	0.006	0.005	-0.006	-0.017***	(0.00)	(-6.03)	(0.00)
<i>RETURN</i> – <i>VW</i>	0.010	0.007	0.006	0.005	-0.006	-0.016***	(0.00)	(-5.93)	(0.00)
<i>MIN</i>	0.026	0.038	0.048	0.060	0.093	0.066***	(0.00)	(60.00)	(0.00)
<i>BETA</i>	0.453	0.635	0.727	0.784	0.733	0.280***	(0.02)	(13.43)	(0.00)
<i>SIZE</i>	19.881	19.749	19.632	19.461	19.071	-0.810***	(0.05)	(-14.66)	(0.00)
<i>BTM</i>	0.863	0.899	0.917	0.897	0.941	0.078***	(0.02)	(2.78)	(0.00)
<i>MOM</i>	0.097	0.096	0.123	0.177	0.349	0.251***	(0.03)	(7.55)	(0.00)
<i>REV</i>	-0.004	-0.006	-0.002	0.005	0.035	0.039***	(0.00)	(7.82)	(0.00)
<i>ILLIQ</i>	0.003	0.001	0.001	0.003	0.013	0.010***	(0.00)	(3.55)	(0.00)
<i>MAX</i>	0.041	0.049	0.055	0.065	0.083	0.041***	(0.00)	(31.18)	(0.00)
<i>VOL</i>	17.423	17.781	17.938	17.981	17.858	0.435***	(0.06)	(6.80)	(0.00)

Table 3: Results for the univariate portfolio analysis - This table presents the average portfolio characteristics for quintile portfolios based on *MIN*. At the end of each month, we sort stocks into quintile portfolios based on *MIN* measures and follow the portfolio returns for the subsequent month. *Low* – *MIN* represents the portfolio consisting of stocks with the lowest extreme negative returns. *High* – *MIN* represents the portfolio consisting of stocks with the highest extreme negative returns. *High* – *Low* represents the zero-cost investment portfolio that mimics an investor's portfolio who has a long position in *High* – *MIN* stocks and a short position of equal size in *Low* – *MIN* stocks. The last three rows respectively denote the Newey and West (1987) standard errors, corresponding t-statistics, and the p-values for the zero cost portfolio (*High* – *Low*). α – *EW* (α – *VW*) is the Fama-French four-factor return premium associated with equally-weighted (value-weighted) portfolios. Similarly, *RETURN* – *EW* (*RETURN* – *VW*) is the expected return associated with equally- (value-) weighted zero-cost portfolios. *SIZE* is the logarithm of the end-of-year market capitalization. *BETA* is the systematic risk factor. *BTM* is the book-to-market ratio. *MOM* is the momentum variable. *REV* is the return reversal measured by the one-month lag returns. *ILLIQ* is the Amihud illiquidity measure (Amihud 2002). *MAX* is the maximum daily return within a month. *VOL* is the natural logarithm of the Turkish Lira-denominated trade volume. ***, **, * indicates statistical significance at a 1%, 5%, and 10% level, respectively.

Panel A: SIZE - MIN portfolios				Panel B: BETA - MIN portfolios				Panel C: MAX - MIN portfolios			
Panel A1: MIN				Panel B1: MIN				Panel C1: MIN			
Small	2	Big		Low - BETA	2	High - BETA		Low - MAX	2	High MAX	
Low - MIN	0.034	0.032	0.029	Low - MIN	0.026	0.033		Low - MIN	0.026	0.033	
2	0.050	0.050	0.045	2	0.043	0.046		2	0.040	0.049	
High - MIN	0.090	0.081	0.072	High - MIN	0.081	0.071		High - MIN	0.063	0.074	
Panel A2: SIZE				Panel B2: BETA				Panel C2: MAX			
Small	2	Big		Low - BETA	2	High - BETA		Low - MAX	2	High - MAX	
Low - MIN	17.803	19.654	21.866	Low - MIN	0.208	0.664		Low - MIN	0.028	0.052	
2	17.801	19.633	21.928	2	0.194	0.691		2	0.031	0.053	
High - MIN	17.680	19.601	21.789	High - MIN	-0.005	0.697		High - MIN	0.032	0.054	
Panel A3: RETURN				Panel B3: RETURN				Panel C3: RETURN			
Small	2	Big		Low - BETA	2	High - BETA		Low - MAX	2	High - MAX	
Low - MIN	0.013	0.023	0.036	Low - MIN	0.040	0.012		Low - MIN	-0.002	0.035	
2	-0.009	0.005	0.013	2	0.019	-0.008		2	-0.037	-0.002	
High - MIN	-0.027	-0.002	0.002	High - MIN	0.006	-0.023		High - MIN	-0.080	-0.043	
High - Low	-0.040***	-0.024***	-0.033***	High - Low	-0.032***	-0.035***		High - Low	-0.077***	-0.078***	
se(High - Low)	(0.00)	(0.00)	(0.00)	se(High - Low)	(0.00)	(0.00)		se(High - Low)	(0.00)	(0.00)	
t(High - Low)	(-8.33)	(-6.06)	(-8.33)	t(High - Low)	(-6.81)	(-9.82)		t(High - Low)	(-26.40)	(-27.48)	
p(High - Low)	(0.00)	(0.00)	(0.00)	p(High - Low)	(0.00)	(0.00)		p(High - Low)	(0.00)	(0.00)	
Panel D1: ILLIQ - MIN portfolios				Panel E: MOM - MIN portfolios				Panel F: VOL - MIN portfolios			
Panel D1: MIN				Panel E1: MIN				Panel F1: MIN			
Low - ILLIQ	2	High - ILLIQ		Low - MOM	2	High - MOM		Low - VOL	2	High - VOL	
Low - MIN	0.032	0.032	0.031	Low - MIN	0.031	0.031		Low - MIN	0.029	0.033	
2	0.048	0.049	0.051	2	0.048	0.047		2	0.046	0.050	
High - MIN	0.076	0.081	0.086	High - MIN	0.078	0.075		High - MIN	0.078	0.081	
Panel D2: ILLIQ				Panel E2: MOM				Panel F2: VOL			
Low - ILLIQ	2	High - ILLIQ		Low - MOM	2	High - MOM		Low - VOL	2	High - VOL	
Low - MIN	0.000	0.000	0.009	Low - MIN	-0.188	0.088		Low - MIN	16.111	17.929	
2	0.000	0.000	0.008	2	-0.205	0.090		2	16.172	17.964	
High - MIN	0.000	0.000	0.028	High - MIN	-0.231	0.095		High - MIN	15.919	17.992	
Panel D3: RETURN				Panel E3: RETURN				Panel F3: RETURN			
Low - ILLIQ	2	High - ILLIQ		Low - MOM	2	High - MOM		Low - VOL	2	High - VOL	
Low - MIN	0.030	0.025	0.023	Low - MIN	0.019	0.026		Low - MIN	0.014	0.030	
2	0.006	-0.001	0.001	2	0.003	0.005		2	-0.010	0.001	
High - MIN	-0.017	-0.011	-0.001	High - MIN	-0.001	0.005		High - MIN	-0.016	-0.007	
High - Low	-0.046***	-0.035***	-0.024***	High - Low	-0.019***	-0.021***		High - Low	-0.032***	-0.037***	
se(High - Low)	(0.00)	(0.00)	(0.00)	se(High - Low)	(0.00)	(0.00)		se(High - Low)	(0.00)	(0.00)	
t(High - Low)	(-10.14)	(-9.2)	(-5.94)	t(High - Low)	(-4.64)	(-5.05)		t(High - Low)	(-8.57)	(-9.45)	
p(High - Low)	(0.00)	(0.00)	(0.00)	p(High - Low)	(0.00)	(0.00)		p(High - Low)	(0.00)	(0.00)	

Table 4: Multivariate portfolio characteristics - This table presents the characteristics of multivariate portfolios. At the beginning of each month, we form three quantile portfolios based on the control characteristic. Then, we divide each quantile into three further groups based on MIN measures. Panels A, B, C, D, E, and F, respectively, denote multivariate portfolios based on SIZE, BETA, MAX, ILLIQ, MOM, and VOL. In each panel, the first subpanel presents the average MIN measures. The second subpanel demonstrates the average control characteristic. The third subpanel presents the expected returns in each portfolio along with the expected returns on the zero-cost multivariate portfolios. The last three rows in the third subpanel denote Newey-West standard errors, t-statistics, and the corresponding p-values for the associated zero-cost portfolio ***, **, * respectively denote statistical significance at 1%, 5%, and 10%.

Panel A: $SIZE - MIN$ portfolios				Panel B: $BETA - MIN$ portfolios				Panel C: $MAX - MIN$ portfolios			
	$Small$	2	Big		$Low - BETA$	2	$High - BETA$		$Low - MAX$	2	$High - MAX$
R^{mkt}	0.307*** (0.053)	0.360*** (0.069)	0.370*** (0.051)	R^{mkt}	0.260*** (0.071)	0.245*** (0.044)	0.196*** (0.049)	R^{mkt}	0.301*** (0.065)	0.234*** (0.035)	0.259*** (0.051)
SMB	0.791*** (0.148)	0.399*** (0.097)	-0.137 (0.120)	SMB	0.579*** (0.216)	0.672*** (0.109)	0.581*** (0.135)	SMB	0.227** (0.094)	0.419*** (0.071)	0.585*** (0.141)
HML	-0.344*** (0.134)	-0.316*** (0.116)	-0.412*** (0.119)	HML	-0.529*** (0.137)	-0.374*** (0.094)	-0.302*** (0.117)	HML	-0.210*** (0.078)	-0.218*** (0.087)	-0.474*** (0.150)
UMD	-0.011 (0.137)	-0.107 (0.146)	-0.007 (0.124)	UMD	-0.068 (0.140)	-0.133 (0.120)	-0.176 (0.129)	UMD	0.002 (0.083)	0.142 (0.092)	-0.071 (0.153)
$\hat{\alpha}$	-0.042*** (0.004)	-0.026*** (0.004)	-0.032*** (0.004)	$\hat{\alpha}$	-0.029*** (0.004)	-0.035*** (0.003)	-0.035*** (0.004)	$\hat{\alpha}$	-0.079*** (0.003)	-0.079*** (0.003)	-0.068*** (0.005)
Observations	226	226	226	Observations	226	226	226	Observations	226	226	226
Adjusted R^2	23%	22%	25%	Adjusted R^2	15%	25%	14%	Adjusted R^2	25%	21%	14%
GRS	50.20	$p(GRS)$	0.00	GRS	54.29	$p(GRS)$	0.00	GRS	374.18	$p(GRS)$	0.00
Panel D: $ILLIQ - MIN$ portfolios				Panel E: $MOM - MOM$				Panel F: $VOL - MIN$ portfolios			
	$Low - ILLIQ$	2	$High - ILLIQ$		$Low - MOM$	2	$High - MOM$		$Low - VOL$	2	$High - VOL$
R^{mkt}	0.334*** (0.060)	0.380*** (0.046)	0.281*** (0.064)	R^{mkt}	0.305*** (0.057)	0.354*** (0.057)	0.384*** (0.058)	R^{mkt}	0.287*** (0.049)	0.315*** (0.064)	0.343*** (0.056)
SMB	0.067 (0.149)	0.673*** (0.100)	0.718*** (0.106)	SMB	0.588*** (0.109)	0.580*** (0.120)	0.674*** (0.147)	SMB	0.757*** (0.153)	0.681*** (0.116)	0.475*** (0.139)
HML	-0.421*** (0.133)	-0.337*** (0.102)	-0.235*** (0.117)	HML	-0.144 (0.112)	-0.252** (0.104)	-0.628*** (0.153)	HML	-0.103 (0.114)	-0.294*** (0.110)	-0.632*** (0.155)
UMD	-0.008 (0.161)	0.157 (0.112)	0.048 (0.118)	UMD	-0.118 (0.154)	0.031 (0.159)	0.138 (0.153)	UMD	0.056 (0.107)	-0.005 (0.120)	0.106 (0.182)
$\hat{\alpha}$	-0.043*** (0.005)	-0.037*** (0.003)	-0.028*** (0.004)	$\hat{\alpha}$	-0.023*** (0.004)	-0.024*** (0.004)	-0.062*** (0.004)	$\hat{\alpha}$	-0.038*** (0.003)	-0.039*** (0.004)	-0.039*** (0.005)
Observations	226	226	226	Observations	226	226	226	Observations	226	226	226
Adjusted R^2	16%	32%	23%	Adjusted R^2	26%	28%	24%	Adjusted R^2	33%	25%	16%
GRS	56.84	$p(GRS)$	0.00	GRS	66.57	$p(GRS)$	0.00	GRS	67.35	$p(GRS)$	0.00

Table 5: **Results for the multivariate factor regressions** - This table presents the results of the following regression on the time series of equally weighted monthly returns of three zero-cost multivariate portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. Panels A, B, C, D, E, and F, respectively, denote multivariate portfolios based on $SIZE$, $BETA$, MAX , $ILLIQ$, MOM , and VOL . In each panel, the corresponding multivariate portfolio is represented in the columns. The rows present the coefficient estimates along with the corresponding Newey-West standard errors in parentheses. The last row in each panel provides the Gibbons et al. (1989) test statistic and the corresponding p-values for the null hypothesis $\hat{\alpha} \equiv \{\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3\} = 0$. ***, **, * represents statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>MIN</i>	-0.307*** (-7.761)	-0.328*** (-8.120)	-0.390*** (-9.012)	-0.384*** (-9.057)	-0.378*** (-9.168)	-0.337*** (-8.460)	-0.342*** (-8.778)	-0.249*** (-6.506)	-0.209*** (-5.642)
<i>BETA</i>	0.00651*** (2.744)	0.00922*** (3.754)	0.00922*** (3.754)	0.00840*** (3.553)	0.00814*** (3.506)	0.00711*** (3.155)	0.00781*** (3.546)	0.00931*** (4.159)	0.0111*** (5.117)
<i>SIZE</i>		-0.00354*** (-4.578)	-0.00303*** (-3.852)	-0.00303*** (-3.852)	-0.00313*** (-4.025)	-0.00295*** (-3.788)	-0.00209*** (-2.763)	-0.00249*** (-3.300)	0.000572 (0.648)
<i>BTM</i>			0.00521*** (3.535)	0.00520*** (3.500)	0.00520*** (3.500)	0.00370*** (2.566)	0.00430*** (3.039)	0.00347*** (2.485)	0.00508*** (3.742)
<i>REV</i>				0.00420 (0.594)	0.00420 (0.594)	0.0184*** (2.733)	0.0189*** (2.808)	0.0190*** (2.818)	0.0188*** (2.807)
<i>MOM</i>						-0.0165*** (-4.495)	-0.0168*** (-4.581)	-0.0164*** (-4.390)	-0.0168*** (-4.479)
<i>ILLIQ</i>							586.1*** (3.617)	600.3*** (3.668)	327.7*** (2.668)
<i>MAX</i>								-0.228*** (-7.419)	-0.184*** (-5.870)
<i>VOL</i>									-0.00548*** (-6.833)
<i>Constant</i>	0.0189*** (3.408)	0.0159*** (3.053)	0.0902*** (4.889)	0.0760*** (4.078)	0.0777*** (4.232)	0.0747*** (4.080)	0.0546*** (3.024)	0.0709*** (3.928)	0.105*** (5.692)
Observations	75,466	75,466	75,466	75,466	75,466	75,466	75,466	75,466	75,466
Number of groups	226	226	226	226	226	226	226	226	226
Standard Errors	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

Table 6: **Firm-level cross-sectional regressions** - This table presents the coefficient estimates from the following model: $RETURN_{s,m+1} = \gamma_{0,m} + \gamma_{1,m}MIN_{s,m} + \sum_{k=2}^9 \gamma'_{k,m}X^k_{s,m} + \varepsilon_{s,m}$. Each month, we regress the stock return on previous months' MIN values along with control variables such as *SIZE*, *BETA*, *BTM*, *MOM*, *REV*, *MAX*, *ILLIQ*, and *VOL*. Entries in the table are the time-series averages of the coefficients obtained from the cross-sectional regressions. Values in parentheses present the corresponding t-statistics obtained from the Newey-West standard errors. ***, **, *, respectively indicates statistical significance at 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>MIN</i>	-0.303*** (-9.030)	-0.321*** (-9.483)	-0.289*** (-7.330)	-0.280*** (-7.124)	-0.282*** (-7.251)	-0.273*** (-7.016)	-0.272*** (-6.989)	-0.190*** (-4.761)	-0.156*** (-3.972)
<i>BETA</i>		0.00578*** (3.861)	0.00733*** (4.209)	0.00755*** (3.670)	0.00762*** (3.727)	0.00742*** (3.661)	0.00738*** (3.640)	0.00765*** (3.746)	0.00851*** (4.136)
<i>SIZE</i>			-0.0361*** (-15.35)	-0.0360*** (-11.98)	-0.0361*** (-12.17)	-0.0350*** (-12.11)	-0.0351*** (-12.09)	-0.0344*** (-11.94)	-0.0300*** (-10.30)
<i>BTM</i>				0.000575 (0.183)	0.000624 (0.200)	0.000789 (0.252)	0.000755 (0.241)	0.000533 (0.170)	0.000819 (0.267)
<i>REV</i>				0.00290 (0.458)	0.00290 (0.458)	0.00590 (0.939)	0.00591 (0.941)	0.00574 (0.916)	0.00528 (0.844)
<i>MOM</i>						-0.00273** (-2.153)	-0.00273** (-2.155)	-0.00261** (-2.109)	-0.00273** (-2.120)
<i>ILLIQ</i>							-0.00662*** (-3.832)	-0.00657*** (-3.732)	-0.00970*** (-4.494)
<i>MAX</i>								-0.175*** (-6.713)	-0.124*** (-4.491)
<i>VOL</i>									-0.00586*** (-5.682)
<i>Constant</i>	0.0241*** (13.69)	0.0213*** (11.84)	0.728*** (15.50)	0.726*** (11.81)	0.728*** (11.99)	0.707*** (11.94)	0.709*** (11.92)	0.700*** (11.86)	0.713*** (11.95)
Observations	93,722	93,696	78,374	76,003	75,987	75,466	75,466	75,466	75,466
Adjusted R^2	18%	18%	20%	20%	20%	20%	20%	20%	21%
F-stat	81.54	46.76	81.58	59.73	53.82	45.23	55.79	54.73	44.40
Firm and Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
S.E.	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Table 7: **Panel regressions** - This table presents the coefficient estimates from the following model: $RETURN_{s,m+1} = \theta_s + \nu_m + \gamma_1 MIN_{s,m} + \sum_{k=2}^9 \gamma'_k X_{s,m}^k + \varepsilon_{s,m}$. We regress the stock return on previous months' *MIN* values along with control variables such as *SIZE*, *BETA*, *BTM*, *MOM*, *REV*, *MAX*, *ILLIQ*, *VOL* along with firm- and time-(year-month) fixed effects, θ_s and ν_m . Values in parentheses present the corresponding t-statistics obtained from standard errors clustered across firm and time. ***, **, * respectively indicates statistical significance at 1%, 5%, and 10%.

Panel A: OLS Standard Errors			
	(1)	(2)	(3)
<i>MIN</i>	-0.264*** (-11.01)	-0.134*** (-4.366)	-0.129*** (-4.116)
<i>MIN</i> × <i>SSR</i>	-0.194*** (-3.730)	-0.178*** (-2.854)	-0.110* (-1.750)
<i>Constant</i>	0.0253*** (18.90)	0.127*** (16.38)	0.757*** (28.53)
Observations	93,722	75,467	75,466
Adjusted R^2	18%	20%	21%
Firm-specific controls	NO	YES	YES
Firm FE	YES	NO	YES
Time FE	YES	YES	YES
Panel B: Clustered Standard Errors			
	(1)	(2)	(3)
<i>MIN</i>	-0.264*** (-7.338)	-0.134*** (-3.138)	-0.129*** (-3.034)
<i>MIN</i> × <i>SSR</i>	-0.194** (-2.250)	-0.178* (-1.777)	-0.110 (-1.155)
<i>Constant</i>	0.0253*** (13.69)	0.127*** (6.561)	0.757*** (12.98)
Observations	93,722	75,467	75,466
Adjusted R^2	18%	20%	21%
Firm-specific controls	NO	YES	YES
Firm FE	YES	NO	YES
Time FE	YES	YES	YES

Table 8: **Pricing of *MIN* under short selling restrictions** - This paper presents the results of the following regression: $RETURN_{s,m+1} = \theta_s + \nu_m + \gamma_1 MIN_{s,m} + \delta_1 (MIN_{s,m} \times SSR_m) + \sum_{k=2}^9 [\gamma_k X_{s,m}^k + \delta_k (X_{s,m}^k \times SSR_m)] + \varepsilon_{s,m}$. SSR_m is a dummy that takes one after February 2020 when the market-wide short-selling ban is first introduced in BIST. $MIN_{s,m}$ is defined as the largest daily loss on stock s within month m . $X_{s,m}^k$ contains firm specific controls: *SIZE*, *BETA*, *BTM*, *MOM*, *REV*, *MAX*, *ILLIQ*, and *VOL*. θ_s and ν_m respectively denote firm and time fixed effects. All firm-specific controls are included with corresponding interactions to allow coefficients to vary with SSR_m . Panel A reports results with OLS standard errors. Panel B reports results with standard errors clustered by firm and time. t-statistics are reported in parentheses. ***, **, *, respectively denote statistical significance at 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)
<i>DAY0</i>	0.00114*** (2.661)	0.00113*** (0.000427)	0.000867** (0.000427)	0.000840* (0.000427)
<i>POST</i>	0.00603*** (18.00)	0.00597*** (0.000332)	0.00579*** (0.000336)	0.00572*** (0.000333)
<i>PRE</i>			-0.00170*** (0.000134)	-0.00178*** (0.000138)
<i>Constant</i>	0.00153*** (24.40)	0.00154*** (6.20e-05)	0.00188*** (6.74e-05)	0.00191*** (6.68e-05)
Observations	89,041,695	89,041,695	89,041,695	89,041,695
Adjusted R^2	0.4%	0.4%	0.4%	0.4%
Investor FE	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES
Month-Year FE	NO	YES	NO	YES
Standard Errors	Clustered	Clustered	Clustered	Clustered

Table 9: **Portfolio changes around minimum return days** - This table presents the results of the regression $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. The values in parentheses present the standard errors that are clustered with respect to investors and stocks. ***, **, *, indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
<i>POST</i>	0.00619*** (0.000340)	0.00412*** (0.000424)	0.00410*** (0.000426)
<i>POST</i> $\times$ <i>GENDER</i>			0.00209*** (0.000341)
<i>DAY0</i>	0.00105** (0.000413)	0.000120 (0.000558)	0.000106 (0.000558)
<i>DAY0</i> $\times$ <i>GENDER</i>			0.000949*** (0.000344)
<i>PRE</i>	-0.00198*** (0.000145)	-0.00111*** (0.000162)	-0.00117*** (0.000163)
<i>PRE</i> $\times$ <i>GENDER</i>			-0.000789*** (0.000143)
<i>Constant</i>	0.00223*** (6.73e-05)	0.000822*** (7.83e-05)	0.00191*** (6.65e-05)
Observations	68,782,562	20,259,133	89,041,695
Sample	Only Male	Only Female	Full Sample
Adjusted R-squared	0.5%	0.3%	0.4%
Investor FE	YES	YES	YES
Stock FE	YES	YES	YES
Month-Year FE	YES	YES	YES
Standard Errors	Clustered	Clustered	Clustered

Table 10: **Portfolio changes across different genders around minimum return days** - This table presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. $GENDER_i$ as an indicator variable equal to one if investor i is male. Columns (1) and (2) present the subsample analyses for male and female investors only. Column (3) presents the interactions. The values in parentheses present the standard errors that are clustered with respect to investors and stocks. ***, **, *, indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
<i>POST</i>	0.00306*** (0.000868)	0.00574*** (0.000333)	0.00574*** (0.000333)
<i>POST</i> $\times$ <i>FOREIGN</i>			-0.00267*** (0.000850)
<i>DAY0</i>	0.000249 (0.00134)	0.000845** (0.000427)	0.000844** (0.000427)
<i>DAY0</i> $\times$ <i>FOREIGN</i>			-0.000580 (0.00128)
<i>PRE</i>	-0.000996 (0.000758)	-0.00179*** (0.000139)	-0.00179*** (0.000139)
<i>PRE</i> $\times$ <i>FOREIGN</i>			0.000882 (0.000820)
<i>Constant</i>	0.000218 (0.000188)	0.00192*** (6.69e-05)	0.00191*** (6.68e-05)
Observations	697,033	88,344,662	89,041,695
Sample	Only Foreign	Only Domestic	Full Sample
Adjusted R-squared	0.003	0.004	0.004
Investor FE	YES	YES	YES
Stock FE	YES	YES	YES
Month-Year FE	YES	YES	YES
Standard Errors	Clustered	Clustered	Clustered

Table 11: **Portfolio changes across foreign and domestic investors around minimum return days** - This table presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,d}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. $FOREIGN_i$ is a dummy variable equal to one if investor i is not domiciled in Turkey. Columns (1) and (2) present the subsample analyses for foreign and domestic investors only. Column (3) presents the interactions. The values in parentheses present the standard errors that are clustered with respect to investors and stocks. ***, **, *, indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>POST</i>	0.00574*** (0.000333)	0.00410*** (0.000426)	0.0150*** (0.00311)	0.0115*** (0.00436)	0.00508*** (0.000432)	0.0184*** (0.00466)
<i>POST</i> × <i>FOREIGN</i>	-0.00267*** (0.000850)					-0.00236*** (0.000852)
<i>POST</i> × <i>GENDER</i>		0.00209*** (0.000341)				0.00203*** (0.000337)
<i>POST</i> × log(<i>AGE</i>)			-0.00249*** (0.000847)			-0.00240*** (0.000873)
<i>POST</i> × log(<i>TENURE</i>)				-0.000792 (0.000594)		-0.000829 (0.000610)
<i>POST</i> × log(<i>NSTOCKS</i>)					0.000365 (0.000214)	0.000418 (0.000218)
<i>DAY0</i>	0.000844** (0.000427)	0.000106 (0.000558)	0.00770*** (0.00271)	0.00807** (0.00407)	0.00233*** (0.000570)	0.0122*** (0.00468)
<i>DAY0</i> × <i>FOREIGN</i>	-0.000580 (0.00128)					0.000256 (0.00134)
<i>DAY0</i> × <i>GENDER</i>		0.000949*** (0.000344)				0.00101*** (0.000337)
<i>DAY0</i> × log(<i>AGE</i>)			-0.00184** (0.000731)			-0.00138 (0.000746)
<i>DAY0</i> × log(<i>TENURE</i>)				-0.000989 (0.000541)		-0.000765 (0.000543)
<i>DAY0</i> × log(<i>NSTOCKS</i>)					-0.000826*** (0.000179)	-0.000795*** (0.000178)
<i>PRE</i>	-0.00179*** (0.000139)	-0.00117*** (0.000163)	-0.00720*** (0.00127)	-0.000540 (0.00243)	-0.00150*** (0.000188)	-0.00504** (0.00241)
<i>PRE</i> × <i>FOREIGN</i>	0.000882 (0.000820)					0.000740 (0.000839)
<i>PRE</i> × <i>GENDER</i>		-0.000789*** (0.000143)				-0.000743*** (0.000145)
<i>PRE</i> × log(<i>AGE</i>)			0.00145*** (0.000335)			0.00147*** (0.000346)
<i>PRE</i> × log(<i>TENURE</i>)				-0.000169 (0.000330)		-0.000186 (0.000335)
<i>PRE</i> × log(<i>NSTOCKS</i>)					-0.000148** (7.46e-05)	-0.000155** (7.53e-05)
log(<i>TENURE</i>)				-0.00259*** (0.000659)		-0.00260*** (0.000664)
log(<i>NSTOCKS</i>)					-0.00216*** (0.000261)	-0.00217*** (0.000262)
<i>Constant</i>	0.00191*** (6.68e-05)	0.00191*** (6.65e-05)	0.00191*** (6.63e-05)	0.0208*** (0.00482)	0.00577*** (0.000473)	0.0248*** (0.00491)
Observations	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695	89,041,695
Adjusted <i>R</i> ²	0.004	0.004	0.004	0.004	0.004	0.004
Investor FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	YES
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Table 12: **Variation in retail investor response around minimum return days** - This table presents the results of interactions with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. We account for investor portfolio diversification through $NSTOCKS_{i,d}$, which is the number of stocks in individual i 's portfolio on day d . $GENDER_i$ as an indicator variable equal to one if investor i is male. $AGE_{i,d}$ denotes the age of investor i on day d . We proxy investor experience, albeit imperfectly, with $TENURE_{i,d}$, defined as the number of days elapsed since the account opening date for investor i as of day d . $FOREIGN_i$ is a dummy variable equal to one if investor i is not domiciled in Turkey. The values in parentheses present the standard errors that are clustered with respect to investors and stocks. ***, **, indicates statistical significance at 1%, and 5%, respectively.

	(1)	(2)	(3)	(4)
<i>POST</i>	0.00446*** (0.000275)	0.00479*** (0.000332)	0.00423*** (0.000274)	0.00456*** (0.000330)
<i>POST</i> $\times$ (<i>High</i> – <i>MIN</i>)	0.00895*** (0.00157)	0.00863*** (0.00159)	0.00880*** (0.00156)	0.00848*** (0.00158)
<i>POST</i> $\times$ (<i>Low</i> – <i>MIN</i>)		-0.00140*** (0.000397)		-0.00140*** (0.000406)
<i>DAY0</i>	0.00136*** (0.000480)	0.00142** (0.000640)	0.00110** (0.000476)	0.00117 (0.000635)
<i>DAY0</i> $\times$ (<i>High</i> – <i>MIN</i>)	-0.00145 (0.000775)	-0.00151 (0.000870)	-0.00164** (0.000773)	-0.00171** (0.000865)
<i>DAY0</i> $\times$ (<i>Low</i> – <i>MIN</i>)		-0.000293 (0.000770)		-0.000301 (0.000768)
<i>PRE</i>			-0.00154*** (0.000131)	-0.00157*** (0.000147)
<i>PRE</i> $\times$ (<i>High</i> – <i>MIN</i>)			-0.00159*** (0.000412)	-0.00156*** (0.000430)
<i>PRE</i> $\times$ (<i>Low</i> – <i>MIN</i>)				0.000151 (0.000240)
(<i>High</i> – <i>MIN</i>)	0.000723*** (0.000154)	0.000594*** (0.000160)	0.00104*** (0.000171)	0.000907*** (0.000178)
(<i>Low</i> – <i>MIN</i>)		-0.000681*** (0.000131)		-0.000705*** (0.000148)
<i>Constant</i>	0.00142*** (7.26e-05)	0.00157*** (6.81e-05)	0.00174*** (7.76e-05)	0.00190*** (7.70e-05)
Observations	89,041,695	89,041,695	89,041,695	89,041,695
Adjusted R^2	0.004	0.004	0.004	0.004
Investor FE	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES
Standard Errors	Clustered	Clustered	Clustered	Clustered

Table 13: **Portfolio changes across *High*–*MIN* and *Low*–*MIN* stocks around minimum return days** - This table presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior* to the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. At the end of each month, we sort stocks into quintile portfolios based on *MIN* measures and follow the portfolio returns for the subsequent month. *Low* – *MIN* represents the portfolio consisting of stocks with the lowest extreme negative returns. *High* – *MIN* represents the portfolio consisting of stocks with the highest extreme negative returns. The values in parentheses present the standard errors that are clustered with respect to investors and stocks. ***, **, indicates statistical significance at 1%, and 5%, respectively.

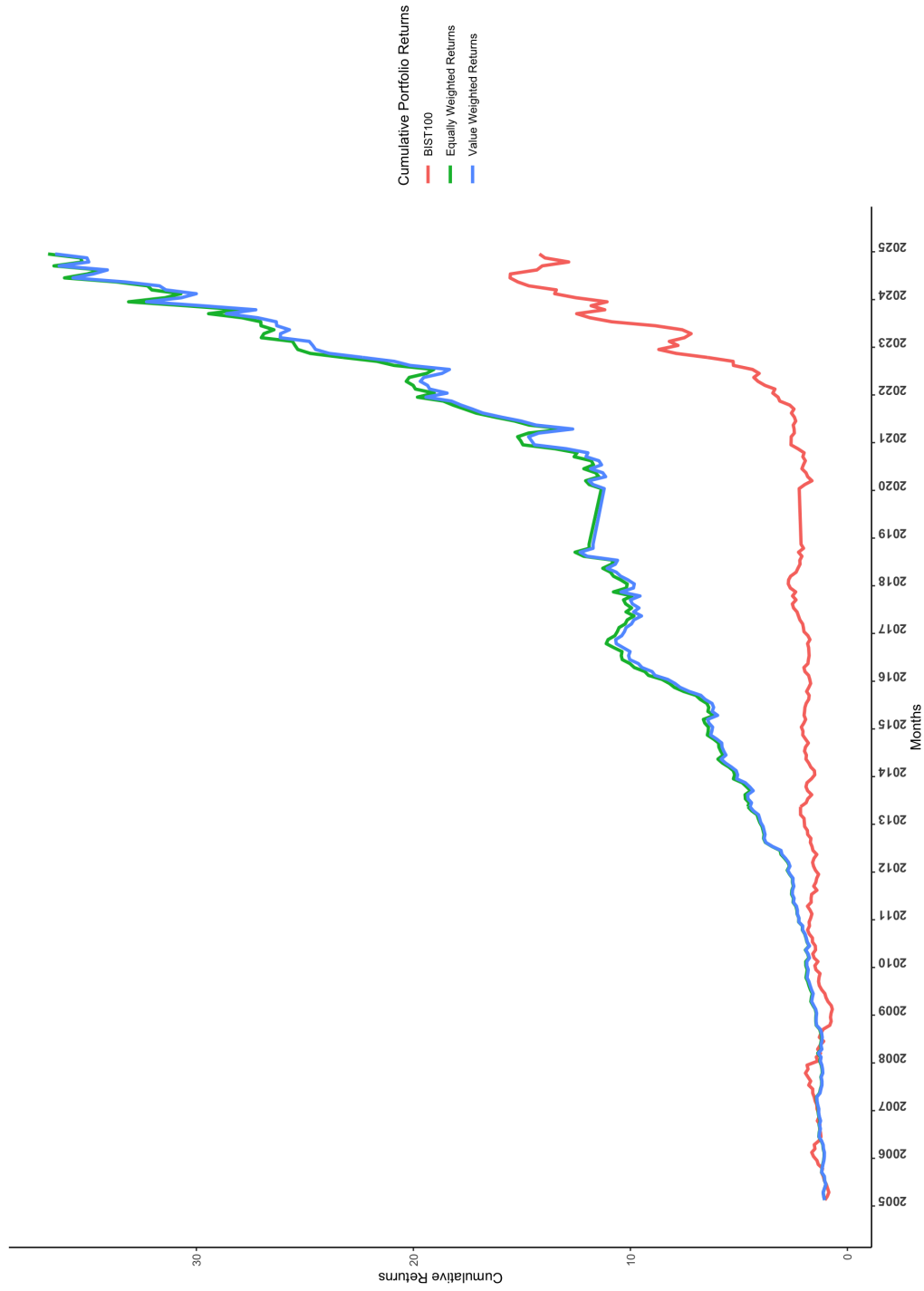


Figure 1: **Cumulative returns for the reverse MIN strategy** - In this figure, we present the cumulative returns for equally-weighted and value-weighted portfolios that mimic an investor who has a long position in *Low* – *MIN* stocks and a short position of equal size in *High* – *MIN* stocks. The benchmark index is BIST100. All returns are denominated in local currency, Turkish Lira.

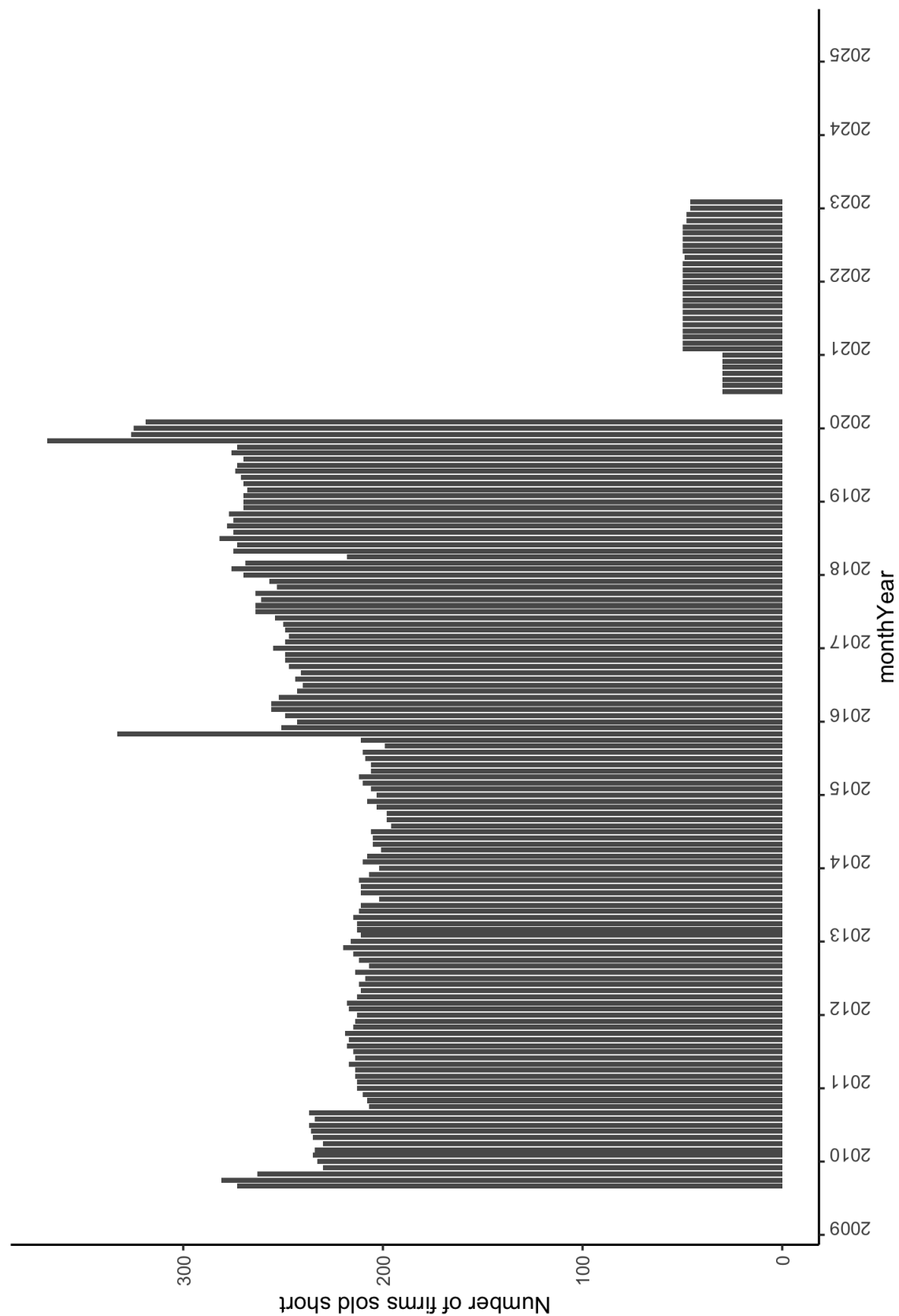


Figure 2: **Short selling restrictions in BIST** - In this figure, we present the number of different BIST firms sold short every month during our sample period.

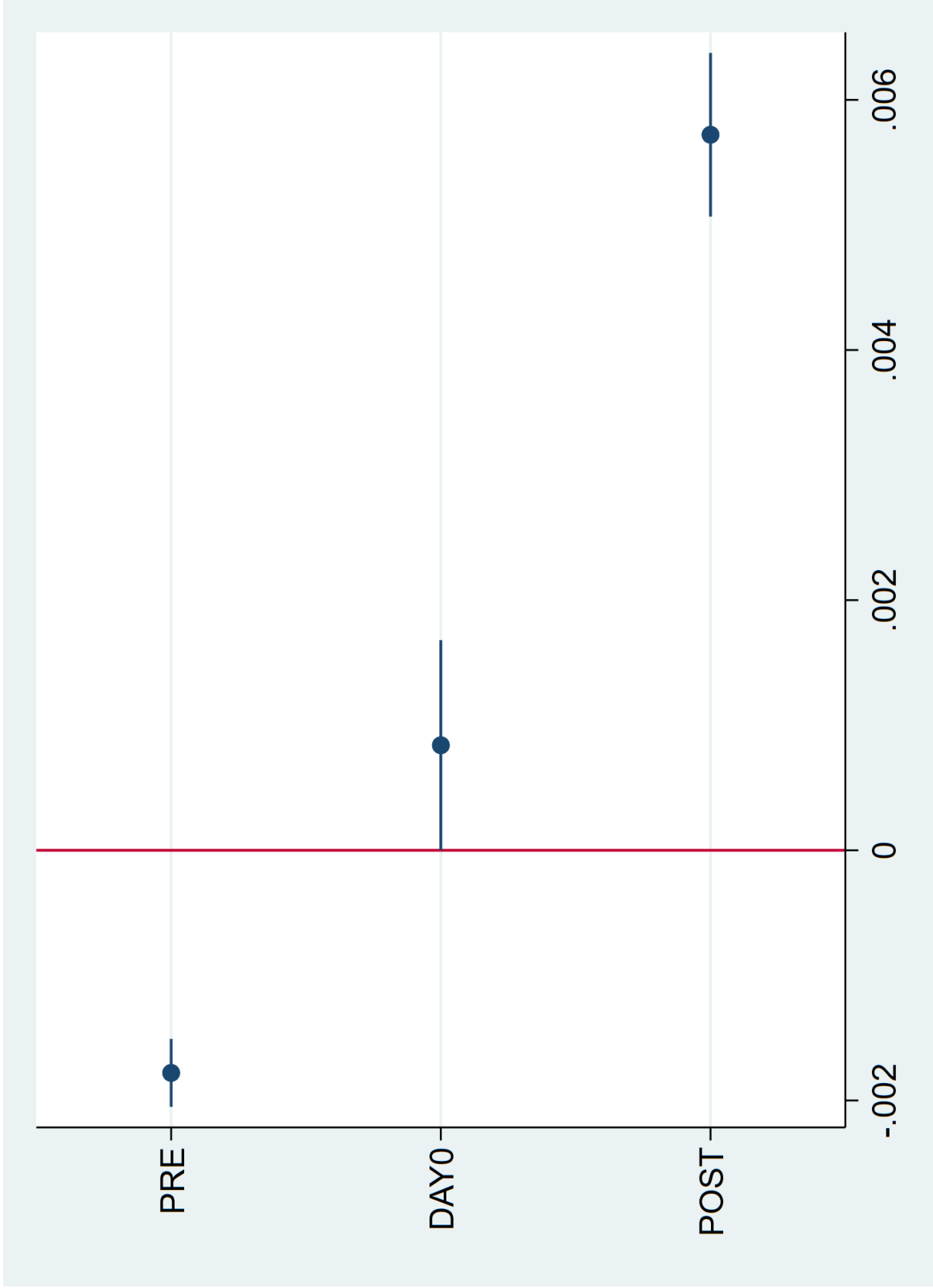


Figure 3: **Portfolio changes around minimum return days** - This figure presents the coefficients of the regression $TRADE_{i,s,d}^m = \alpha_i + \theta_s + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}^m$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. The standard errors are clustered with respect to investors and stocks.

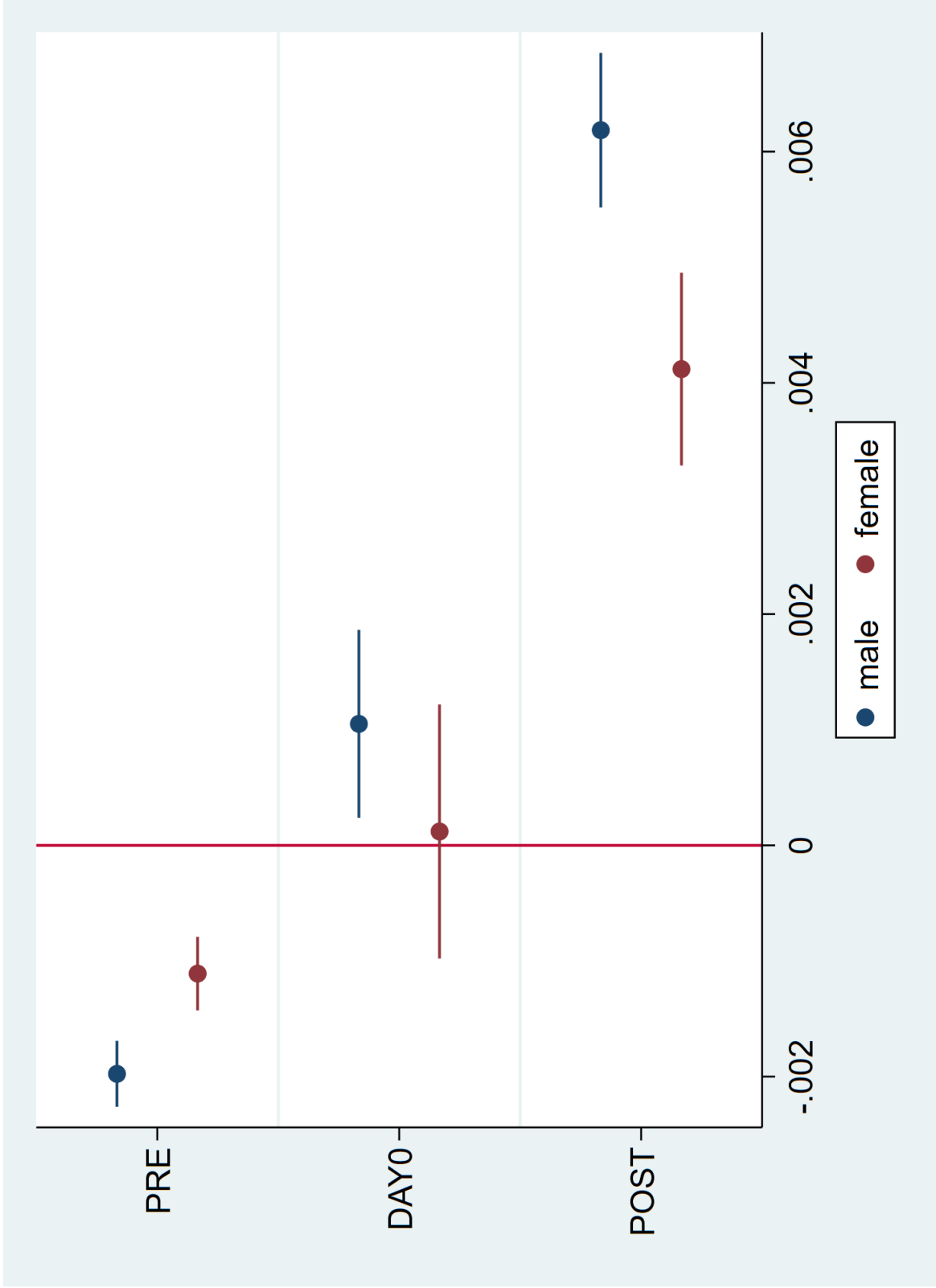


Figure 4: **Portfolio changes across different genders around minimum return days** - This figure presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days prior to the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days after the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. $FOREIGN_i$ is a dummy variable equal to one if investor i is not domiciled in Turkey.

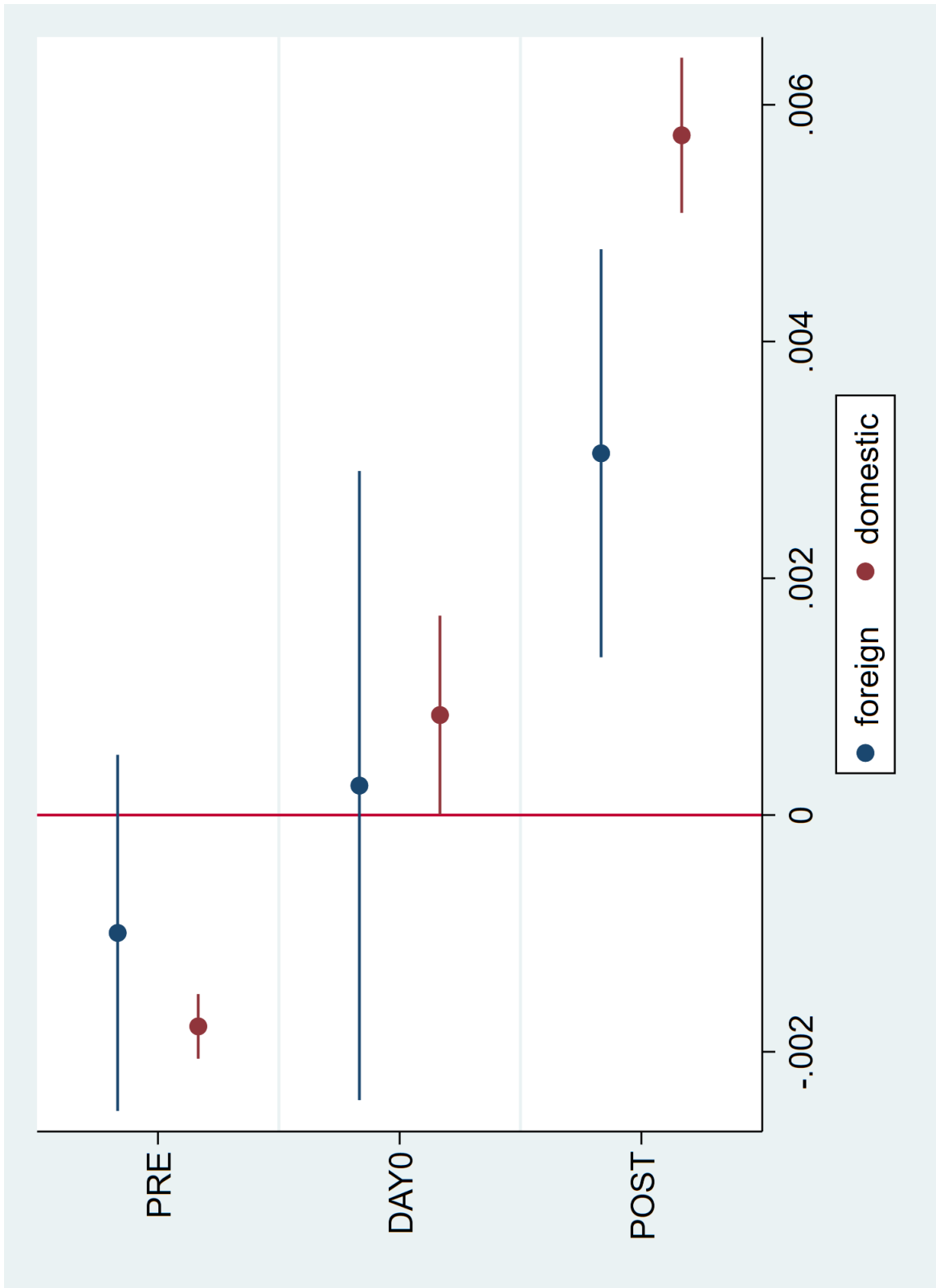


Figure 5: **Portfolio changes across foreign and domestic investors around minimum return days** - This figure presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. $GENDER_i$ as an indicator variable equal to one if investor i is male.

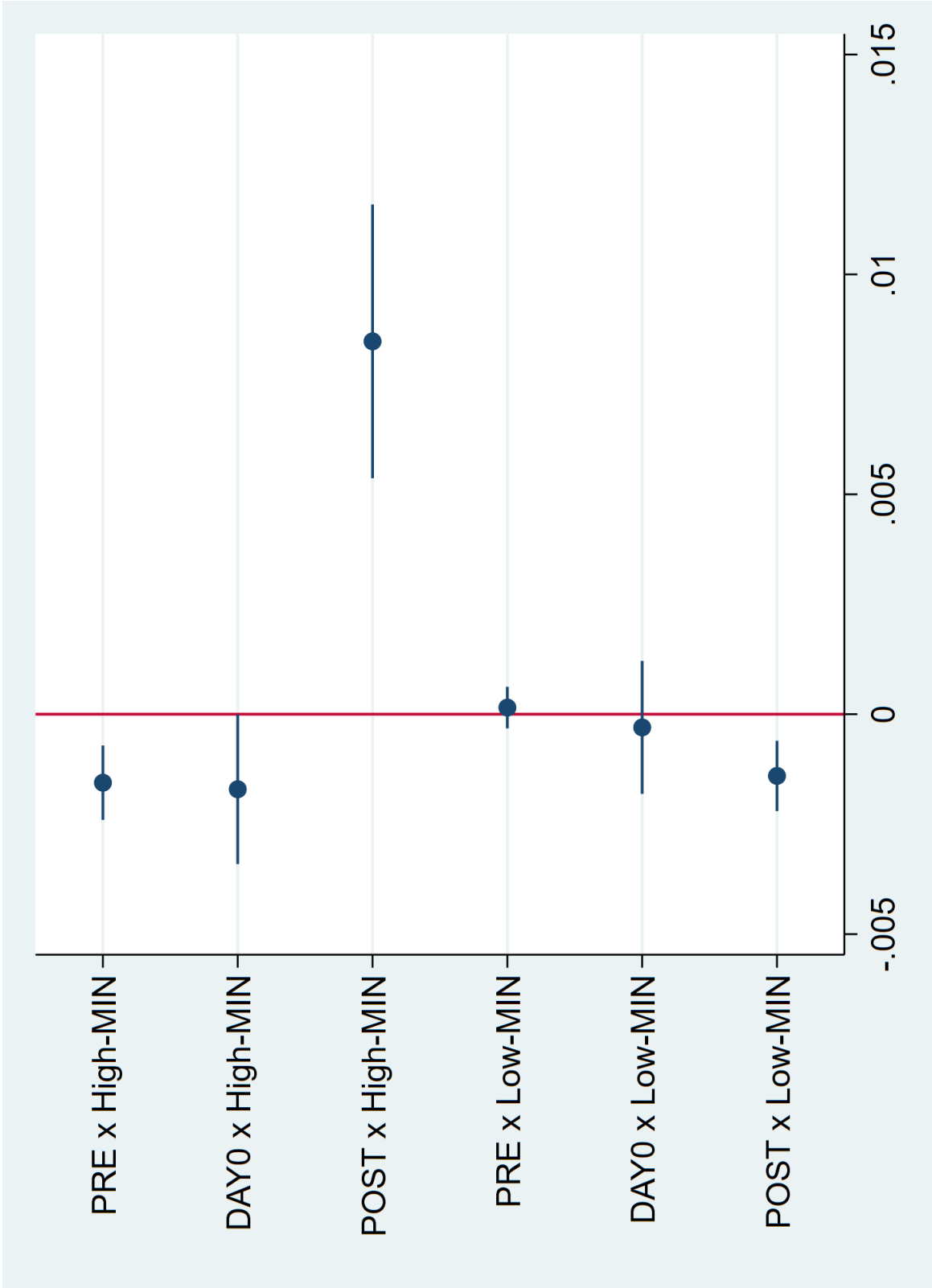


Figure 6: **Portfolio changes after extreme negative returns** - This figure presents the results of subsample analyses with the regression model $TRADE_{i,s,d} = \alpha_i + \theta_s + \gamma_m + \beta_1 PRE_{s,d}^m + \beta_2 DAY0_{s,d}^m + \beta_3 POST_{s,d}^m + \varepsilon_{i,s,t}$. $TRADE_{i,s,d}$ is 1 (-1) if investor i , purchases (sells) stock s on trading day d . $DAY0_{s,d}^m$ is a dummy that takes one on the minimum daily return day d for stock s in month m , and zero otherwise. $PRE_{s,d}^m$ is a dummy that takes one for five days *prior to* the minimum daily return date for stock s in month m , and zero otherwise. $POST_{s,d}^m$ is a dummy that takes one for five days *after* the date the minimum daily return for stock s in month m is observed. α_i , θ_s , and γ_m respectively denote investor, stock, and time (year-month) fixed effects. At the end of each month, we sort stocks into quintile portfolios based on MIN measures and follow the portfolio returns for the subsequent month. *Low* - MIN represents the portfolio consisting of stocks with the lowest extreme negative returns. *High* - MIN represents the portfolio consisting of stocks with the highest extreme negative returns.

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Appendix

Multivariate Portfolio Analyses with IVOL

For each stock s in month m , the idiosyncratic volatility levels, $IVOL_{s,m}$, is defined as the standard deviations of the residuals $(e_{s,d})$ obtained from the market model, presented in equation (1), that is,

$$IVOL_{s,m} = \sqrt{\text{var}(e_{s,d})} \quad d = \{1, \dots, D_m\}.$$

where D_m represents the number of trading days in month m . Table A1 presents the average portfolio characteristics for 3×3 *IVOL* – *MIN* portfolios. We observe that across each *IVOL* quantile, the return on the zero-investment portfolios is statistically significant at a 1 % level. The average return associated with zero-investment portfolios varies between -5% and -12%, indicating that the impact is also economically significant. We obtain similar results for the return premiums associated with multivariate *IVOL* – *MIN* portfolios. Specifically, in Table A2, we observe that the premiums associated with zero-investment portfolios are all negative and statistically significant at a 1% level. Specifically, estimates of the intercept terms vary between -6% and -12%. We also reject the null hypothesis that all intercept terms are jointly equal to zero, with a GRS test statistic equaling 370.56, which indicates statistical significance at a 1% level. Hence, the *MIN* effect seems to yield statistically and economically significant return premiums even after controlling for the variation in firm-level idiosyncratic risk.

Panel A: <i>MIN</i>			
	<i>Low – IVOL</i>	2	<i>High – IVOL</i>
<i>Low – MIN</i>	0.025	0.034	0.046
2	0.038	0.049	0.069
<i>High – MIN</i>	0.052	0.067	0.107
Panel B: <i>IVOL</i>			
	<i>Low – IVOL</i>	2	<i>High – IVOL</i>
<i>Low – MIN</i>	0.012	0.020	0.032
2	0.013	0.021	0.035
<i>High – MIN</i>	0.014	0.021	0.044
Panel C: <i>RETURN</i>			
	<i>Low – IVOL</i>	2	<i>High – IVOL</i>
<i>Low – MIN</i>	0.009	0.039	0.104
2	-0.022	-0.009	0.04
<i>High – MIN</i>	-0.046	-0.044	-0.019
<i>High – Low</i>	-0.054***	-0.081***	-0.123***
se(<i>High – Low</i>)	(0.00)	(0.00)	(0.00)
t(<i>High – Low</i>)	(-19.70)	(-28.37)	(-25.59)
p(<i>High – Low</i>)	(0.00)	(0.00)	(0.00)

Table A1: **Multivariate *IVOL – MIN* portfolio characteristics** - This table presents the characteristics of multivariate *IVOL – MIN* portfolios. At the beginning of each month, we form three quantile portfolios based on the *IVOL*. Then, we divide each *IVOL* quantile into three further groups based on *MIN* measures. Panel A presents the average *MIN* measures. Panel B demonstrates the average *IVOL* values. Panel C presents the expected returns in each portfolio along with the expected returns on the zero-cost multivariate portfolios. The last three rows in Panel denote Newey-West standard errors, t-statistics, and the corresponding p-values for the associated zero-cost portfolio ***, **, * respectively denote statistical significance at 1%, 5%, and 10%.

	<i>Low – IVOL</i>	2	<i>High – IVOL</i>
R^{mkt}	0.303*** (0.050)	0.154*** (0.049)	0.122** (0.061)
SMB	-0.036 (0.085)	-0.102 (0.085)	0.620*** (0.162)
HML	-0.103 (0.074)	-0.262*** (0.098)	-0.427*** (0.146)
UMD	-0.015 (0.069)	-0.005 (0.093)	-0.0003 (0.180)
$\hat{\alpha}$	-0.056*** (0.002)	-0.079*** (0.003)	-0.120*** (0.005)
Observations	226	226	226
Adjusted R^2	32%	7%	9%
GRS	370.56	p(GRS)	0.00

Table A2: **Multivariate factor regressions for $IVOL - MIN$** - This table presents the results of the following regression on the time series of equally weighted monthly returns of three zero-cost $IVOL - MIN$ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. The rows present the coefficient estimates along with corresponding Newey-West standard errors in parentheses. The last row provides the Gibbons et al. (1989) test statistic and the corresponding p-values for the null hypothesis $\hat{\alpha} \equiv \{\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3\} = 0$. ***, **, * represents statistical significance at 1%, 5%, and 10% levels, respectively.