Skewed to lose? Idiosyncratic Return Asymmetry in the Swedish Equity Market

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Abstract

This paper examines whether and how idiosyncratic return asymmetry is priced in the Swedish equity market. The question is motivated by mixed prior evidence, which may reflect differences in how asymmetry is measured as well as the possibility that any asymmetry premium is conditional rather than uniform across markets and firms. Using the density-based measure of residual asymmetry (RA) developed by Chen and Liu (2024), the paper tests whether stocks with greater upside asymmetry earn lower future returns in Sweden. It further examines whether this measure contains information beyond conventional skewness- and lottery-based proxies and whether the effect is stronger where arbitrage is more constrained. The results show a negative relation between RA and subsequent stock returns. A central finding is that the effect is concentrated in small growth stocks. In the full sample, the relation also becomes more visible when liquidity is poor, arbitrage costs are high, and when broader macro and sentiment conditions are more uncertain. Conventional idiosyncratic skewness adds little once RA is included, suggesting that the density-based measure captures distributional information not reflected in third moment skewness. A trading-cost analysis further shows that gross return spreads are positive, but net returns turn negative once implementation costs are applied. These results are more consistent with a limits-to-arbitrage interpretation than with a broad asymmetry risk-premium explanation. Overall, the results suggest that asymmetry is priced in a smaller European market, but in a way that is more conditional, more friction-sensitive, and less easily tradable than the strongest U.S. evidence would imply.

Keywords: idiosyncratic return asymmetry; density-based asymmetry; stock returns; asset pricing; limits to arbitrage

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1 Introduction

Investors may care not only about expected return and risk, but also about the asymmetry of stock returns. Stocks with positively asymmetric or lottery-like payoffs may attract greater investor demand than standard mean-variance theory would predict. In rational asset-pricing models, this idea appears through the role of skewness in portfolio payoffs (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000). In behavioral models, it appears through probability weighting and investor demand for lottery-like outcomes (Tversky and Kahneman, 1992; Barberis and Huang, 2008). Both perspectives imply that stocks with more favorable upside asymmetry may become overpriced and earn lower subsequent returns. However, empirical evidence on this relation remains mixed especially outside the U.S. market studies.

One reason for the mixed evidence may be measurement. Much of the earlier literature relies on third moment skewness or on simpler lottery proxies such as extreme positive daily returns. Although these measures are informative, they may capture the relevant aspect of firm-level return asymmetry imperfectly. This issue motivates the contribution of Chen and Liu (2024) and Chen, Liu and Zhang (2025), who propose a density-based measure of idiosyncratic return asymmetry, RA, based on the shape of the empirical return density around its mode. In the U.S. market, they show that stocks with greater upside asymmetry earn lower returns and that this relation is more robust than traditional skewness-based results. Their framework therefore provides a useful basis for re-examining whether and how asymmetry is priced outside the U.S., and for testing whether the relation also holds in a smaller European market such as Sweden.

This paper therefore applies the RA framework to the Swedish equity market. The central research question is whether idiosyncratic return asymmetry is priced in Sweden, and if so, whether the relation is distinct from conventional skewness- and lottery-based effects and stronger where arbitrage is more constrained. Sweden provides an informative setting for this question because, although it has one of the most active equity markets in Europe relative to its economic size, it remains much smaller and more concentrated than the U.S. market. It also combines substantial institutional participation with a strong household equity culture (OECD, 2025). These features make Sweden a relevant setting for examining whether asymmetry-related return predictability exists outside the original U.S. setting, whether it is weaker or more conditional in a smaller market and whether it is concentrated in market segments where arbitrage is more difficult.

We find that density-based idiosyncratic return asymmetry, RA, is negatively related to future stock returns in Sweden, but that the effect is conditional rather than broad. The relation is clearest in equally weighted portfolios and stronger for the 12-month than for the 24-month based measure. A central result is that the effect is concentrated in small growth stocks rather than in small stocks or growth stocks more generally. The evidence also shows that RA contains information beyond traditional skewness- and lottery-based proxies. The effect becomes more visible when liquidity is poor, and volatility and arbitrage costs are high. Furthermore, the effect is stronger during periods of elevated economic policy uncertainty. This matters for interpretation. If the relation primarily reflected a broad premium for asymmetry risk, one would expect it to appear more uniformly across firms and market states. Instead, the Swedish evidence shows that the relation is strongest in environments and segments where corrective trading is more difficult. Although high-RA stocks are on average larger and have higher book-to-market ratios in the Swedish sample, the pricing results show that the negative RA-return relation is not strongest among large or value-oriented firms. Instead, it appears most clearly among small growth stocks and in high-friction states, especially when liquidity is poor and arbitrage costs are high. This suggests that the average cross-sectional characteristics of high-RA stocks and the conditions under which RA is most strongly priced should be distinguished.

This suggests that the RA effect is more closely tied to trading frictions and the persistence of mispricing than to a uniform compensation for asymmetry risk. A trading-cost analysis further shows that gross return spreads are positive, but net returns turn negative once implementation costs are applied. Overall, the results suggest that asymmetry is priced in a smaller European market, but in a way that is more conditional, more sensitive to frictions, and less easily tradable than the strongest U.S. evidence would imply.

2 Literature Review

2.1 Theoretical Foundations Behind Asymmetry Pricing

The relation between return asymmetry and expected returns can be explained by both rational asset-pricing theory and behavioral models. In rational models, investors care about the effect of individual securities on the distribution of portfolio payoffs. Kraus and Litzenberger (1976) show in the three-moment capital asset pricing model that skewness matters for asset prices in addition to mean and variance. In their framework, assets that reduce the skewness of aggregate wealth by performing poorly in bad states of the world should offer higher expected returns. On the other hand, assets that contribute favorable skewness may command a premium and earn lower expected returns. Harvey and Siddique (2000) provide empirical support for this idea. Using conditional coskewness, they show that stocks that perform especially poorly when the market experiences negative shocks should offer higher expected returns as compensation for downside asymmetry.

Behavioral models imply the same sign for the asymmetry-return relation under a different reasoning. Under cumulative prospect theory, investors overweight small probabilities and may therefore place high value on positively skewed payoffs (Tversky and Kahneman, 1992). Barberis and Huang (2008) show that this probability-weighting behavior can make lottery-like securities attractive even when they offer low average returns. Mitton and Vorkink (2007) further argue that heterogeneous skewness preferences can generate equilibrium under diversification, while Kumar (2009) shows that individual investors are more likely to hold lottery-type stocks. These studies suggest that positively asymmetric stocks may become overpriced because they offer a small probability of a large gain rather than hedging aggregate risk.

These two explanations imply the same prediction for stock returns. Stocks with more favorable upside asymmetry may earn lower future returns. However, they imply different mechanisms. In the rational framework, the relation reflects compensation for downside risk. In the behavioral framework, it reflects mispricing driven by investor demand for upside potential. This distinction is important because a mispricing-based explanation implies that the asymmetry effect should be stronger where arbitrage is costly, while a risk-based explanation is more consistent with a broader and more uniform pattern across stocks.

2.2 U.S. Empirical Evidence on Return Asymmetry

Much of the U.S. empirical literature examines whether firm-level asymmetry predicts future stock returns. One strand focuses on skewness-based measures. Boyer, Mitton and Vorkink (2010) study expected idiosyncratic skewness, which captures asymmetry in firm-specific returns after removing common factor exposure. They find a robust negative relation between expected skewness and future returns. Their evidence suggests that investors are willing to pay for upside potential at the individual stock level, consistent with behavioral models of lottery demand in 2.1. A related strand uses simpler proxies for lottery-type payoffs. Bali, Cakici and Whitelaw (2011) show that the maximum daily return over the prior month, MAX, is a strong negative predictor of future stock returns. Stocks that have recently experienced an extreme positive daily return subsequently underperform, which they interpret as evidence that investors overvalue lottery-like payoff profiles. These studies provide U.S. evidence that upside asymmetry is associated with lower subsequent returns, even when measured in different ways.

2.3 Why is the Empirical Literature Mixed?

Despite strong theoretical motivation and substantial empirical support, the literature points to no single uniform asymmetry premium. One reason is that studies differ in how asymmetry is measured. Some focus on coskewness (Harvey and Siddique (2000), others on idiosyncratic skewness (Boyer, Mitton and Vorkink (2010)) and others on extreme-return proxies such as MAX (Bali, Cakici and Whitelaw (2011)). More recent work uses density-based measures such as RA (Chen et al. (2025)). Although these approaches are related, they capture different dimensions of return distributions. The mixed evidence may therefore arise partly because these studies test different aspects of return asymmetry.

A second reason concerns measurement quality within a given asymmetry framework. Chen et al. (2025) argue that traditional third moment skewness may be too limited a proxy for firm-level return asymmetry. In this view, weak or inconsistent evidence may reflect measurement error rather than the absence of a pricing relation.

A third explanation is that asymmetry-related premia may be state-dependent rather than universal. Shleifer and Vishny (1997) argue that arbitrage is risky and constrained in practice. Stambaugh, Yu and Yuan (2012) show that many anomalies are stronger following high-sentiment periods, when overpricing is harder to correct because of short-sale frictions. Applied to asymmetry, this suggests that any negative relation between upside asymmetry and future returns may be strongest in speculative segments of the market, particularly among small, illiquid or difficult-to-arbitrage stocks. This perspective is important because it implies that a weak unconditional result should not be interpreted as evidence that asymmetry is irrelevant. Instead, the effect may be concentrated in regimes or market segments where mispricing is more likely to persist.

2.4 Density-Based Idiosyncratic Asymmetry

Chen and Liu (2024) and Chen et al. (2025) propose an alternative approach to measuring firm-level return asymmetry that departs from conventional moment-based methods. Rather than summarizing the return distribution through its third moment, their measure, RA, characterizes the shape of the idiosyncratic return density around its mode. Intuitively, the measure asks whether the residual return distribution is thicker on the upside or on the downside relative to its most likely outcome. A positive value of RA indicates that the distribution places relatively more mass on the right side of the mode, while a negative value indicates relatively more mass on the left side. In this sense, RA extends beyond extreme observations in the tails. Instead, it measures asymmetry from the overall shape of the return distribution around its center. This feature is important because traditional third moment skewness can be sensitive to outliers and may be estimated imprecisely over shorter horizons. By contrast, the density-based approach is designed to capture asymmetry more directly from the distribution itself.

Applied to U.S. equities, Chen et al. (2025) find that RA negatively predicts future stock returns in both portfolio sorts and Fama-MacBeth regressions. The relation is persistent and survives a comprehensive set of controls[1] and conventional skewness measures. The robustness to conventional skewness controls is particularly relevant for the present paper, as it suggests that RA captures distributional information that is not fully summarized by third moment statistics.

Chen et al. (2025) provide both an empirical benchmark and a measurement framework. This paper closely follows their density-based approach to examine whether the asymmetry-return relation is present in the Swedish market and whether it is more clearly identified than under traditional skewness-based measures. If the mixed evidence in smaller markets partly reflects measurement limitations, RA should perform better than traditional proxies even outside the U.S. If the relation is instead genuinely weaker in smaller markets for structural reasons, improving the measure will not be sufficient to recover it.

2.5 Evidence in Europe and Smaller Markets

Evidence outside the U.S. is useful because it speaks to the external validity of asymmetry-related return predictability. In Europe, Annaert, De Ceuster and Verstegen (2013) find that stocks with more extreme positive returns subsequently earn lower returns, consistent with lottery-like overpricing. Walkshäusl (2014) similarly documents a negative MAX effect in European equities. These studies suggest that lottery demand mechanisms are not limited to the U.S. market.

At the same time, the European evidence is mixed. Annaert, De Ceuster and Van Cappellen (2023) show that average skewness does not significantly predict future stock market returns in the euro area, even when alternative horizons and estimators are considered. This suggests that skewness-based predictability may vary across markets. More broadly,

[1] Firm size, book-to-market, momentum, idiosyncratic volatility, coskewness, MAX, MIN, mean reversal, beta, Abnormal turnover, illiquidity

evidence from smaller or less liquid markets points to heterogeneity in how asymmetry-related effects appear across different market settings.

Although Sweden has one of the most active equity markets in Europe relative to its economic size (OECD, 2025), it remains much smaller and more concentrated than the U.S. market. This may limit the aggregate scale of the retail lottery demand documented by Kumar (2009). At the same time, Sweden combines substantial institutional participation with a comparatively strong household equity culture (OECD, 2025). Relatively high institutional ownership may dampen the overpricing of positively skewed stocks if institutional investors are less prone to the probability-weighting behavior emphasized in cumulative prospect theory. However, Sweden's substantial retail investor base and long tradition of direct household equity ownership may still sustain lottery-type preferences at the margin.

The Swedish setting is informative because it allows us to examine whether the asymmetry-return relation extends beyond the U.S. and whether a density-based measure is more informative than traditional skewness-based proxies in a market where earlier evidence may be weaker or more conditional.

2.6 Trading Frictions and Economic Viability

While the existing literature mainly examines whether asymmetry predicts future returns, it pays less attention to whether any related premium remains economically meaningful after trading costs. Novy-Marx and Velikov (2016) show that the net profitability of cross-sectional anomalies depends strongly on turnover and portfolio construction. Lower-turnover strategies are more likely to remain profitable after transaction costs, while high-turnover strategies are more easily offset by implementation frictions. This issue is important in our setting because the asymmetry-based portfolios are updated monthly and may therefore generate substantial turnover. The issue may be even more important in Sweden, where the stock market is smaller and less liquid than in the U.S. For this reason, this paper examines not only whether asymmetry predicts future returns, but also whether any documented return spread remains economically meaningful after trading frictions.

2.7 Contribution and Hypotheses

This paper contributes to the literature in four ways. First, it examines whether idiosyncratic return asymmetry is priced in a smaller European market. Most of the strongest evidence on asymmetry-related return predictability comes from the U.S., while the evidence from Europe and other smaller markets is more mixed.

Second, the paper contributes to the measurement literature on asymmetry. Prior evidence is mixed partly because different studies examine different asymmetry concepts and partly because conventional third moment skewness may be a noisy proxy. This paper therefore applies the density-based measure proposed by Chen and Liu (2024) to test whether asymmetry is priced more clearly when it is measured using the full shape of the return distribution rather than a traditional skewness statistic.

Third, the paper contributes to the literature on mispricing and limits to arbitrage. Prior research suggests that return anomalies may vary across firms and market states. If investors overpay for upside asymmetry and arbitrage is costly, then any asymmetry premium may be concentrated in market segments where corrective trading is more difficult. The Swedish setting allows us to test the average asymmetry-return relation and to examine whether that relation is stronger under low liquidity, high arbitrage costs and related conditions.

Fourth, the paper contributes by evaluating the economic implementability of exploiting a potential mispricing caused by idiosyncratic return asymmetry after trading costs. While the gross return spreads may show that the asymmetry effect is economically meaningful before costs, the net-return analysis may be largely offset once turnover and trading frictions are incorporated.

This paper tests the following hypotheses:

Hypothesis 1: Density-based idiosyncratic return asymmetry, RA, is negatively related to future stock returns in Sweden.

Hypothesis 2: The predictive content of RA is not fully absorbed by traditional skewness measures or other lottery-related proxies.

Hypothesis 3: The negative RA-return relation is more pronounced in smaller stocks.

Hypothesis 4: The negative RA-return relation is stronger among stocks facing greater arbitrage frictions, as proxied by illiquidity and idiosyncratic volatility.

3 Data and Methodology

3.1 Data

For Sweden, the longest possible sample period is 1983-2022 due to limited availability of treasury-bill data. However, data quality issues in the sample limit the sample period to 2000-2022 (see Appendix A). A potential consequence of a shorter time frame is that it limits direct comparability with Chen et al. (2025) and may reduce statistical power[2]. A shorter sample however is still prioritized to reduce the negative impact of noise, measurement error and inconsistencies in the underlying data.

Stock market data is obtained from FinBas on the Stockholm Stock Exchange. Both A, B and preference share classes are retained and treated as separate securities to increase the number of usable observations and preserve potential differences in liquidity, voting rights and pricing across share classes. The risk-free rate is proxied by the Swedish 1-month Treasury bill rate from Riksbanken's statistical database. We use the 1-month bill because it has historically been more liquid than longer maturity Treasury bills (Aytug, Fu and Sodini, 2020). To align with the daily return data, the annualized yield is converted into a daily risk-free rate and merged into the stock return panel. We then construct the value weighted market return series using our existing sample of stocks listed on the Stockholm Stock Exchange[3]. The final data panel is then constructed by calculating excess returns for the individual securities and the market.

During the mechanism tests we further obtain Economic Policy Uncertainty data from an indicator developed by professors from Stanford University for both Sweden and globally (Baker, Bloom, & Davis, n.d.).

3.2 Main Methodology

For the main empirical analysis, we follow Chen et al. (2025) and construct residual asymmetry (RA). RA is estimated from daily excess-return residuals derived from a quadratic market model and is intended to capture asymmetry more comprehensively than conventional third moment skewness measures.

3.2.1 Key variables

Table 1: Key Variables

Table 1: This table presents the key variables and control variables used in the analysis of this paper. Column 1 denotes the variable abbreviation used throughout and subsequent columns denote a short definition and formula if needed.

Variable	Name	Definition and formulas
R	Excess return	Monthly stock return of stock i minus the 1-month t bill. $$R^e_{i,t} = R_{i,t} - r_{f,t}$$
IVOL	Idiosyncratic volatility	Standard deviation of daily idiosyncratic returns within month t, obtained from: $$R_{i,d} = \gamma_{1i} + \gamma_{2i} R_{m,d} + \varepsilon_{i,d}$$ $$IVOL_{i,t} = \sqrt{\operatorname{var}(\varepsilon_{i,d})}, \quad d = 1, \dots, D_t$$
ISKEW	Idiosyncratic skewness	Skewness of daily residuals $\varepsilon_{i,d}$ computed over the past 12 months
BETA	Market beta	Coefficient γ_{2i} from annual regression:

[2] Chen et al. (2025) use a 59 yearlong period between August 1963 to December 2022.

[3] 98% correlation with OMXSPI downloaded from Refinitiv Eikon

		$R_{i,d} = \gamma_{1i} + \gamma_{2i} R_{m,d} + \varepsilon_{i,d}$ Updated annually using all trading days in the year.
COSKEW	Coskewness	Following Harvey and Siddique (2000), co-movement of stock return with squared market return over 12 months: $COSKEW_{i,t} = \frac{\frac{1}{D_t}\sum_{d=1}^{D_t}(R_{i,d} - \bar{R}_i)(R_{m,d} - \overline{R_m})^2}{\sqrt{\left(\frac{1}{D_t}\sum_{d=1}^{D_t}(R_{i,d} - \bar{R}_i)^2\right)\left(\frac{1}{D_t}\sum_{d=1}^{D_t}(R_{m,d} - \overline{R_m})^2\right)}}$
MAX	Maximum Return	Following Bali et al. (2011), maximum daily excess return in month t: $MAX_{i,t} = \max(R_{i,d}), \quad d = 1, \dots, D_t$
MIN	Maximum Return	Following Bali et al. (2011), negative of the minimum daily excess return in month t: $MIN_{i,t} = -\min(R_{i,d}), \quad d = 1, \dots, D_t$
MV	Market Value	Natural logarithm of market capitalization at the end of month t.
BM	Book-to-Market	Following Fama & French (1993), natural logarithm of the book-to-market ratio at end of month t. Book value is from the previous fiscal year-end (lagged 6 months); market value is from the prior December.
MOM	Momentum	Following Jegadeesh & Titman (1993), cumulative return from month $t-7$ to month $t-1$ (six months, skipping the most recent month).
REV	Reversal	Following Jegadeesh (1990), excess return of stock i in the prior month t−1.
TURN	Turnover	Average daily share turnover over the past month, where daily turnover = share trading volume/total shares outstanding.
ILLIQ	Illiquidity	Following Amihud (2002), average ratio of absolute daily price change to daily trading volume: $ILLIQ_{i,t} = \frac{1}{N_{i,t}}\sum_{d=1}^{N_{i,t}}\frac{\lvert r_{i,d}\rvert}{TV_{i,d}}$
ALIQ	Aggregate Market Liquidity	$ALIQ_t = -\frac{1}{N_t}\sum_{i=1}^{N_t} ILLIQ_{i,t}$
ARSMV	Aggregate Volatility Measure	$ARSMV_t = \sqrt{\frac{1}{N_t - 1}\sum_{d=1}^{N_t}(rm\_excess_{d,t} - \overline{rm\_excess}_t)^2}$

3.2.2 Estimating Residuals: The Quadratic Market Model

The quadratic market model is used to separate the market component from the idiosyncratic residual in an individual security. Diversified investors can eliminate systematic risk through portfolio construction and should therefore primarily care about asymmetry in the firm specific return distribution, the idiosyncratic component. Following Chen and Liu (2024), Chen et al. (2025), Harvey and Siddique (2000) and Bali et al. (2011), idiosyncratic returns are extracted using the quadratic market model:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{m,t}^2 + \varepsilon_{i,t} \qquad (1)$$

where $R_{i,t}$ is the excess return of stock i on day t, $R_{m,t}$ is the market excess return on the same day and $\varepsilon_{i,t}$ is the idiosyncratic return. The inclusion of the squared market return $R_{m,t}^2$ serves two purposes. First, it captures nonlinear dynamics between individual stock returns and the market. Second, the estimated slope coefficient i directly measures systematic asymmetry or coskewness, cleanly separating it from the idiosyncratic component.

3.2.3 Measurement of Idiosyncratic Return Asymmetry

We then estimate residual asymmetry nonparametrically from the distribution of daily idiosyncratic residuals. X denotes the residual return distribution for a given stock over the estimation window. In population form, return asymmetry is defined as:

$$RA = sign(M_X) \int_0^\infty \left(f(M+s)^{\left(\frac{1}{2}\right)} - f(M-s)^{\left(\frac{1}{2}\right)} \right)^2 ds \qquad (2)$$

where $f(\chi)$ denotes the probability density function and M is the mode of X. Because both the density and the mode are unknown, they are estimated nonparametrically using kernel density estimation. The kernel estimator provides a smooth estimate of the shape of the residual return distribution, which is then used to identify the mode and measure asymmetry around it. The estimated density is given by (see Appendix B for kernel settings):

$$\widehat{f_n}(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{X_i - x}{h}\right) \qquad (3)$$

where n is the number of observations, $k(\cdot)$ is the kernel function and h is the bandwidth parameter. The estimated mode is then obtained as:

$$\widehat{\mathrm{M_n}} = \arg\max_{\mathrm{x} \in \mathbb{R}} \widehat{\mathrm{f_n}}(\mathrm{x}) \qquad (4)$$

Using these estimates, the sample analogue of return asymmetry is computed as:

$$\widehat{RA} = \mathrm{sign}\left(\widehat{M_n}\right) \int_0^\infty \left(\widehat{f_n}\left(\widehat{M_n} + s\right)^{1/2} - \widehat{f_n}\left(\widehat{M_n} - s\right)^{1/2} \right)^2 ds \qquad (5)$$

In our implementation, this procedure is carried out at the end of each month using daily residuals from a rolling estimation window. In the baseline specification, RA for month t is constructed from residuals over the preceding 12 months, spanning months $t - 11$ through t. As a robustness check, we additionally construct RA using a 24-month rolling window based on residuals from months $t - 23$ through t.

A stock month is included in the estimation only if the stock has at least 200 nonzero return observations during the previous 250 trading days. The nonzero return screen helps ensure that stale pricing doesn't affect the residual estimation. Chen et al. (2025) additionally impose a minimum price filter of $8. In our main specification, we do not apply a price filter to preserve sample size.

3.3 Portfolio Sorts

3.3.1 Univariate Portfolio Sorts

To examine whether idiosyncratic return asymmetry predicts future stock returns, we conduct univariate portfolio sorts following Chen et al. (2025). At the end of each month t, stocks are sorted into portfolios based on their estimated RA. In the baseline specification, portfolios are formed using RA estimated over the previous 12 months of daily data, while a 24-month estimation window is used as an additional robustness check. We form both quintile and decile portfolios and compute returns over the subsequent one-month holding period. To assess whether the results depend on portfolio weighting, we report both equal weighted and value weighted portfolio returns. Lastly, a zero-cost long-short portfolio is constructed where the highest RA portfolio is a long position while the low RA portfolio is shorted.

Formally, let $P_{J,t}$ denote portfolio P formed at the end of month t, where $J = 1, \ldots, J$ and $J5, J10$, depending on whether quintile or decile portfolios are used. The equal weighted return on portfolio J in month $t + 1$ is given by:

$$R_{j,t+1}^{EW} = \frac{1}{N_{j,t}} \sum_{i \in P_{j,t}} R_{i,t+1} \tag{6}$$

where $N_{j,t}$ denotes the number of stocks in portfolio j at the end of month t. The value weighted return is given by:

$$R_{j,t+1}^{VW} = \sum_{i \in P_{j,t}} w_{i,t} R_{i,t+1}, \qquad w_{i,t} = \frac{MV_{i,t}}{\sum_{k \in P_{j,t}} MV_{k,t}} \tag{7}$$

Where $MV_{i,t}$ denotes the market value of stock i at the end of month t. The zero-cost return spread is then constructed as:

$$R_{t+1}^{LS} = R_{J,t+1} - R_{1,t+1} \tag{8}$$

where RJ, $t + 1$ is the return on the portfolio with the highest RA and R1, $t + 1$ is the return on the portfolio with the lowest RA.

Following the benchmark design, we further evaluate the performance of the RA sorted portfolios using standard factor models. In addition to reporting average portfolio returns, we estimate abnormal returns relative to the CAPM, the Fama-French three factor model and the Carhart four-factor model. In the latter case, momentum is constructed from the Swedish stock universe using local portfolio sorts, allowing us to estimate Carhart-style four-factor alphas. For each portfolio j, factor adjusted performance is obtained from timeseries regressions of monthly excess portfolio returns on the relevant factor returns. Under the CAPM, the regression is

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_{MKT,j}\left(R_{M,t} - R_{f,t}\right) + \varepsilon_{j,t}, \tag{9}$$

Under the Fama-French three-factor model,

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_{MKT,j}\left(R_{M,t} - R_{f,t}\right) + \beta_{SMB,j}SMB_t + \beta_{HML,j}HML_t + \varepsilon_{j,t}, \tag{10}$$

And under the four-factor specification,

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_{MKT,j}\left(R_{M,t} - R_{f,t}\right) + \beta_{SMB,j}SMB_t + \beta_{HML,j}HML_t + \beta_{MOM,j}MOM_t + \varepsilon_{j,t}. \tag{11}$$

The intercept a_j measures the abnormal return, or alpha, of portfolio j relative to the corresponding factor model. We report these alphas both for the individual RA sorted portfolios and for the zero-cost high-minus-low portfolio. This allows us to assess whether the return spread associated with RA reflects compensation for common systematic risk factors or instead represents abnormal return predictability that remains after standard risk adjustment.

Further, the momentum factor MOM_t is constructed from monthly 2×3 size-momentum portfolios following Carhart-style conventions, where momentum is measured using cumulative returns over the past 12 months excluding the most recent month.

3.3.2 Bivariate Portfolio Sorts

Additionally, we conduct a bivariate portfolio sort following Chen et al. (2025). At the end of each month, stocks are first sorted into groups based on a control characteristic X and then within each control group sorted again on RA. This examines whether the return spread associated with RA persists after conditioning on other dimensions of the cross-section.

In the baseline specification, we implement dependent sorts in which stocks are first allocated into quintiles according to the control variable X and subsequently into quintiles according to RA within each control portfolio. For each month, we then compute the average future one-month return for the resulting 5 by 5 portfolios. To summarize the pricing effect of RA, we calculate within each control quintile the return difference between the highest-RA and lowest-RA portfolio and then average these differences across the five control groups. As in the univariate sorts, we report both equal weighted and value weighted returns. The pricing effect is calculated as follows:

$$R_{q,t+1}^{LS} = R_{q,5,t+1} - R_{q,1,t+1} \tag{12}$$

where $R_{q,5,t+1}$ and $R_{q,1,t+1}$ denote the returns in month t+1 on the highest-RA and lowest-RA portfolios, respectively, within control characteristic quintile q.

The overall bivariate return spread is then computed as

$$R_{t+1}^{BIV} = \frac{1}{5}\sum_{q=1}^{5} R_{q,t+1}^{LS} \tag{13}$$

The set of control characteristics is chosen to capture well established cross-sectional return predictors and variables closely related to lottery-like payoffs or limits to arbitrage. We examine whether the RA effect remains after controlling for firm size, book-to-market, momentum, market beta, turnover, illiquidity, idiosyncratic volatility, idiosyncratic skewness, coskewness, maximum daily return, minimum daily return and short-term reversal.

3.4 Fama-MacBeth Regressions

To complement the portfolio sort evidence, we estimate Fama-MacBeth (1973) cross-sectional regressions to examine whether idiosyncratic return asymmetry predicts future stock returns at the firm level after controlling for other return related characteristics. This approach provides a parametric test of the pricing relation associated with RA and allows us to assess whether the information captured by RA is distinct from that contained in established anomaly variables.
In each month t, we estimate the following cross-sectional regression:

$$R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}. \tag{14}$$

Where X is,

$$X_{i,t} = \begin{pmatrix} MV_{i,t}, BM_{i,t}, MOM_{i,t}, BETA_{i,t}, TURN_{i,t}, ILLIQ_{i,t}, IVOL_{i,t}, ISKEW_{i,t}, COSKEW_{i,t}, \\ MAX_{i,t}, MIN_{i,t}, REV_{i,t} \end{pmatrix}. \tag{15}$$

where $R_{i,t+1}$ is the one-month-ahead return on stock i, $RA_{i,t}$ is the idiosyncratic return asymmetry measure constructed at the end of month t and $X_{i,t}$ is a vector of control variables measured at the end of month t. The controls are the same as in the bivariate return.

The dependent variable is the stock return realized in month t+1. The key explanatory variable is $RA_{i,t}$ measured using the residual return distribution estimated over the preceding 12 months in the baseline specification. As a robustness check, we also repeat the analysis using an alternative 24-month measure of RA.

After estimating the cross-sectional regression separately in each month, we compute the Fama-MacBeth estimate of each coefficient as the time series average of the corresponding monthly slope coefficients:

$$\overline{\beta_{RA}} = \frac{1}{T}\sum_{t=1}^{T} \beta_{RA,t} \tag{16}$$

Statistical significance is assessed using time series t-statistics based on the sequence of monthly coefficient estimates. The t-statistic is given by

$$t\left(\overline{\beta_{RA}}\right) = \frac{\overline{\beta_{RA}}}{\sqrt{\widehat{\mathrm{Var}}\left(\overline{\beta_{RA}}\right)}} \tag{17}$$

Where $\sqrt{\widehat{\mathrm{Var}}\left(\overline{\beta_{RA}}\right)}$ is estimated using Newey-West standard errors to account for potential autocorrelation in the monthly coefficient series.

The Fama-MacBeth framework serves two purposes in the analysis. First, it tests whether RA retains explanatory power for future returns once multiple characteristics are controlled for simultaneously. Second, it provides a complementary perspective to the portfolio sorts by imposing a linear cross-sectional structure on the relation between RA and expected returns. If the coefficient on RA remains negative and statistically significant in these regressions, this would indicate that stocks with more positively asymmetric idiosyncratic return distributions earn lower subsequent returns even after accounting for a broad set of competing predictors.

4 Empirical Results

4.1 Descriptive Statistics

4.1.1 Summary Statistics and Pearson Correlation

Table 2: Summary statistics and variable correlation

This table presents descriptive statistics and pairwise Pearson correlations for the main variables used in the empirical analysis. Panel A reports the mean, median, standard deviation and number of observations for each variable. Panel B reports Pearson correlation coefficients. Variable definitions are as follows: RA is the residual-based measure of return asymmetry; MV is firm size reported in logged terms; BM is book-to-market reported in logged terms; MOM is momentum; BETA is the market beta; TURN is turnover; ISKEW is idiosyncratic skewness; IVOL is idiosyncratic volatility; ILLIQ is the Amihud illiquidity measure; COSKEW is coskewness; MAX and MIN are the maximum and minimum daily returns within the month; and REV is short-term reversal. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Panel A: Summary Statistics

	RA	**MV**	**BM**	**MOM**	**BETA**	**TURN**	**ISKEW**	**IVOL**	**ILLIQ**	**COSKEW**	**MAX**	**MIN**	**REV**
Mean	-0.010	7.490	-0.311	0.072	0.749	0.009	0.620	0.023	1.970	-0.160	0.056	0.047	0.009
Median	-0.009	7.445	-0.476	0.047	0.719	0.002	0.451	0.019	0.006	-0.112	0.043	0.037	0.004
Sd	0.016	2.126	1.319	0.346	0.398	0.058	1.341	0.016	32.657	0.288	0.047	0.034	0.122
N	82077	72359	72359	82077	82077	77956	82077	81832	80952	82077	82077	82077	82077

Panel B: Pearson correlation

	RA	**MV**	**BM**	**MOM**	**BETA**	**TURN**	**ISKEW**	**IVOL**	**ILLIQ**	**COSKEW**	**MAX**	**MIN**	**REV**
RA	**1.000**	0.155	0.076	-0.160	-0.004	-0.035	-0.223	-0.148	-0.043	0.070	-0.151	-0.055	-0.075
MV	0.155	**1.000**	-0.268	0.126	0.377	-0.253	-0.218	-0.453	-0.260	-0.056	-0.306	-0.306	0.061
BM	0.076	-0.268	**1.000**	-0.126	-0.040	0.420	-0.062	-0.085	0.029	0.006	-0.085	-0.049	-0.056
MOM	-0.160	0.126	-0.126	**1.000**	-0.047	-0.016	0.187	-0.107	-0.084	-0.034	-0.090	-0.098	0.061
BETA	-0.004	0.377	-0.040	-0.047	**1.000**	0.114	-0.029	-0.011	-0.097	-0.016	0.067	0.106	-0.039
TURN	-0.035	-0.253	0.420	-0.016	0.114	**1.000**	0.044	0.119	-0.014	0.013	0.120	0.106	0.003
ISKEW	-0.223	-0.218	-0.062	0.187	-0.029	0.044	**1.000**	0.225	0.086	0.057	0.252	0.055	0.097
IVOL	-0.148	-0.453	-0.085	-0.107	-0.011	0.119	0.225	**1.000**	0.298	0.085	0.857	0.754	-0.052
ILLIQ	-0.043	-0.260	0.029	-0.084	-0.097	-0.014	0.086	0.298	**1.000**	0.055	0.219	0.247	-0.051
COSKEW	0.070	-0.056	0.006	-0.034	-0.016	0.013	0.057	0.085	0.055	**1.000**	0.085	0.057	-0.012
MAX	-0.151	-0.306	-0.085	-0.090	0.067	0.120	0.252	0.857	0.219	0.085	**1.000**	0.485	-0.061
MIN	-0.055	-0.306	-0.049	-0.098	0.106	0.106	0.055	0.754	0.247	0.057	0.485	**1.000**	-0.038
REV	-0.075	0.061	-0.056	0.061	-0.039	0.003	0.097	-0.052	-0.051	-0.012	-0.061	-0.038	**1.000**

In Table 2, Panel A reports summary statistics for the main variable (RA) and key control variables used in this study. The average value of RA is slightly negative, with a mean of -0.010 and a median of -0.009 suggesting that in the sample, observations tend to be more negatively skewed than positively skewed. Since both the mean and the median are close to 0, the overall distributions seem to be centered near symmetry.

Looking at the firm-characteristic variables of market value and book-to-market, the summary statistics indicate cross-sectional heterogeneity in both firm size and valuation. Logged market value (MV) has a mean of 7.490, a median of 7.445, and a standard deviation of 2.126, suggesting a wide dispersion in firm size across the sample. Similarly, logged book-to-market (BM) has a mean of -0.311, a median of -0.476, and a standard deviation of 1.319, indicating considerable variation in relative valuation across firms. The median being more negative than the mean for BM also suggests that the distribution is somewhat asymmetric, with a larger share of firms clustered at lower book-to-market values.

Observing the alternative asymmetry measures such as ISKEW and COSKEW, the mean and median of ISKEW are positive at 0.620 and 0.451 respectively. This contrasts with the negative skew of RA and indicates that these two variables capture different dimensions of return asymmetry. COSKEW on the other hand is negative on average with a mean of -0.160 and a median of -0.112, implying that stocks tend to co-vary more strongly with the market in downside states than in upside states.

In Table 2, Panel B reports the Pearson correlation matrix. Focusing on RA, the measure appears to be only weakly to moderately correlated with the control variables. RA is negatively correlated with several, ISKEW (-0.223), IVOL (-0.148), MAX (-0.151), momentum (-0.160), and reversal (-0.075) which indicates that RA is capturing information that is not fully absorbed by the control variables. Moreover, RA is positively correlated with MV and BM, with coefficients of 0.155 and 0.076 respectively, which indicates that stocks with higher RA on average tend to be larger and have higher book-to-market ratios.

For the control variables, correlations are generally modest, suggesting that multicollinearity is unlikely to be a major empirical concern. The highest correlated variables are IVOL and MAX (0.857), IVOL and MIN (0.754) and MAX and MIN (0.485). Thus, stocks with higher idiosyncratic volatility are also more likely to have more extreme return realizations.

Some moderately strong correlations are between MV and IVOL (-0.453), BM and TURN (0.420) which suggests that larger firms tend to exhibit lower idiosyncratic volatility and that higher book-to-market firms tend to have higher turnover.

4.1.2 Average Portfolio Characteristics

Table 3 (Page 18) reports the average portfolio characteristics for decile portfolios sorted on RA from low to high and the control variables. Firstly, it should be noted that almost all the High-Low spreads are statistically significant which indicates that stocks with different levels of return asymmetry exhibit systematically different characteristics.

Observing the firm-characteristic variables MV and BM, the High-RA decile is characterized by significantly larger market value and higher book-to-market ratios than the Low-RA decile. Specifically, MV increases from 6.980 in the lowest RA portfolio to 7.998 in the highest, while BM rises from -0.491 to -0.146. Momentum also declines markedly across the sort, from 0.177 to -0.018. These patterns suggest that high-RA stocks are on average, larger, less growth-oriented and associated with weaker prior momentum.

Looking at the trading-related characteristics, turnover, illiquidity, and idiosyncratic volatility all decline significantly across the RA sort. TURN falls from 0.010 in the lowest RA decile to 0.006 in the highest, ILLIQ declines from 5.917 to 2.106, and IVOL decreases from 0.027 to 0.021. This indicates that high-RA stocks are associated with lower trading activity, lower price-impact illiquidity, and lower idiosyncratic volatility than low-RA stocks. Thus, this suggests that high-RA stocks in the Swedish market are not characterized by the conventional profile of highly volatile and strongly illiquid speculative stocks as seen in Chen et al. (2025). Instead, relative to low-RA stocks, they appear less volatile and less illiquid, even though their turnover is also lower.

Also notably, idiosyncratic skewness declines sharply across the RA sort falling from 0.960 in the lowest RA decile to -0.146 in the highest, with a highly significant High-Low spread of -1.106. This suggests that RA captures a dimension of asymmetry that is distinct from conventional idiosyncratic skewness.

4.1.3 Persistence of RA

Next, we examine whether RA behaves as a persistent measure rather than noise. To do so, we construct monthly transition matrices (following Chen et al. (2025)) for both the 12-month and 24-month RA measures. At the end of each month, stocks are sorted into deciles based on their estimated RA and their decile assignments are compared with those in month $t + 1$. The transition matrix is then formed by averaging one-month transition frequencies across the full sample period.

Table 4 (Page 18) shows the transition matrix for the 12-month RA measure and suggests that RA is a persistent firm characteristic. The largest probabilities are concentrated along the main diagonal, which indicates that stocks tend to remain in the same RA decile from one month to the next rather than being randomly reassigned across the distribution. This pattern is especially strong in the tails. Stocks in the lowest RA decile remain in Port1 with a probability of 67.78%, while stocks in the highest decile remain in Port10 with a probability of 65.60%. The 24-month transition matrix points in the same direction with even greater persistence. The diagonal probabilities are higher than for the 12-month measure, especially in the extreme deciles, which indicates that the longer estimation window produces a smoother ranking of firms.

The matrix also shows that when stocks do move, they tend to move to nearby portfolios rather than across the full distribution. Stocks in Port1 move to Port2 with a probability of 19.37%, but the probabilities of jumping directly to the highest deciles are close to zero. A similar pattern appears at the upper end of the distribution where stocks in Port10 move most often to Port9 with a probability of 14.48%. Transitions from Port10 to the lowest deciles are very rare. This concentration around the diagonal suggests that month-to-month changes in RA are generally incremental.

Table 3: Portfolio Characteristics sorted on RA

Table 3: This table reports average firm characteristics for portfolios formed by sorting stocks on RA. At the end of each month, stocks are sorted into deciles based on RA, where Low denotes the portfolio with the lowest RA and High denotes the portfolio with the highest RA. The table reports the time series average of the cross-sectional mean of each characteristic within each RA portfolio. The High-Low row reports the difference between the highest-RA and lowest-RA portfolios for each characteristic, with t-statistics reported in parentheses. Variable definitions are as follows: RA is the residual-based measure of return asymmetry; MV is firm size reported in logged terms; BM is book-to-market reported in logged terms; MOM is momentum; BETA is the market beta; TURN is turnover; ISKEW is idiosyncratic skewness; IVOL is idiosyncratic volatility; ILLIQ is the Amihud illiquidity measure; COSKEW is coskewness; MAX and MIN are the maximum and minimum daily returns within the month; and REV is short-term reversal. The sample period is 2000-01-03 to 2022-12-31. *, * and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Data sources: FinBas, Riksbanken

	RA	MV	BM	MOM	BETA	TURN	ILLIQ	IVOL	ISKEW	COSKEW	MAX	MIN	REV
Low	-0.040	6.980	-0.491	0.177	0.777	0.010	5.917	0.027	0.960	-0.155	0.070	0.050	0.025
2	-0.022	6.865	-0.457	0.139	0.751	0.010	2.790	0.027	1.005	-0.145	0.069	0.050	0.020
3	-0.016	6.967	-0.422	0.108	0.751	0.010	3.436	0.026	0.982	-0.142	0.066	0.050	0.016
4	-0.013	7.127	-0.396	0.079	0.746	0.007	2.171	0.025	0.866	-0.142	0.062	0.049	0.011
5	-0.010	7.281	-0.329	0.057	0.743	0.008	1.751	0.024	0.797	-0.137	0.059	0.048	0.009
6	-0.008	7.459	-0.264	0.057	0.743	0.008	1.908	0.023	0.722	-0.141	0.056	0.047	0.010
7	-0.006	7.667	-0.257	0.050	0.733	0.008	1.285	0.021	0.633	-0.133	0.052	0.044	0.007
8	-0.003	7.933	-0.199	0.032	0.734	0.006	0.784	0.020	0.374	-0.133	0.047	0.043	0.003
9	0.002	8.097	-0.131	0.005	0.750	0.007	0.602	0.019	-0.060	-0.131	0.045	0.044	-0.003
High	0.015	7.998	-0.146	-0.018	0.765	0.006	2.106	0.021	-0.146	-0.125	0.048	0.047	-0.006
High-Low	**0.054*** **	**1.019*** **	**0.345*** **	**-0.195*** **	**-0.013**	**-0.004*** **	**-3.810*** **	**-0.007*** **	**-1.106*** **	**0.030*** **	**-0.021*** **	**-0.003*** **	**-0.032*** **
	(86.56)	*(17.11)*	*(9.22)*	*(-14.18)*	*(-0.87)*	*(-4.04)*	*(-3.41)*	*(-10.80)*	*(-30.94)*	*(5.05)*	*(-13.25)*	*(-2.58)*	*(-13.17)*

Table 4: Transition matrix persistence test

Table 4: This table presents transition matrices for RA-sorted decile portfolios and is used to assess the persistence of the RA characteristic over time where each cell denotes the percentage of stocks that stay within its previous month sorted decile. Stocks are sorted each month into deciles based on RA. The reported values show the percentage of stocks that remain in, or move to, a given RA decile in the subsequent reclassification period of $t+1$ compared to t. Panel A uses the RA estimated over a window of 12 months and Panel B uses RA estimated from 24 months. In column 1, Low denotes the portfolio with the lowest RA and High denotes the portfolio with the highest RA. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

	Panel A: 12-month based RA transition matrix									**Panel B: 24-month based RA transition matrix**										
	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**
Low	**67.70**	19.42	5.66	2.40	1.51	0.84	0.55	0.36	0.29	1.26	**78.51**	16.67	2.47	0.69	0.43	0.42	0.22	0.20	0.06	0.36
2	19.81	**43.39**	20.86	7.47	3.58	1.72	1.01	0.50	0.34	1.33	15.85	**55.56**	20.06	4.89	1.60	0.71	0.33	0.20	0.13	0.67
3	5.91	20.33	**35.42**	20.13	8.55	4.16	1.89	1.06	0.48	2.05	2.51	19.24	**46.71**	21.52	5.84	1.91	0.75	0.30	0.20	1.02
4	2.14	7.74	19.23	**32.85**	19.68	8.62	4.27	1.94	1.10	2.44	1.11	4.51	20.51	**41.91**	21.76	6.17	2.20	0.72	0.19	0.92
5	1.46	3.33	8.61	18.87	**31.17**	19.61	8.48	3.62	2.10	2.75	0.41	1.39	5.58	20.97	**40.33**	20.83	6.22	1.80	0.62	1.84
6	0.77	2.18	3.81	8.78	19.11	**32.09**	19.27	7.26	3.56	3.18	0.23	0.73	1.99	5.96	20.18	**41.34**	20.74	5.31	1.41	2.11
7	0.52	0.90	2.24	4.32	8.85	19.14	**35.45**	18.93	6.23	3.41	0.19	0.30	0.74	1.98	6.52	20.37	**43.92**	19.75	3.57	2.65
8	0.29	0.49	0.94	1.49	3.41	7.25	19.77	**46.16**	16.50	3.70	0.18	0.11	0.32	0.81	1.68	5.02	19.77	**52.76**	16.37	2.97
9	0.28	0.22	0.48	1.14	1.88	3.31	6.37	16.67	**54.69**	14.96	0.11	0.10	0.20	0.21	0.41	1.27	3.45	16.62	**66.28**	11.34
High	1.39	1.43	2.21	2.59	2.83	2.88	2.94	3.72	14.50	**65.51**	0.46	0.65	1.13	1.11	1.66	1.93	2.73	2.90	10.99	**76.44**

4.2 Does Residual Asymmetry Predict Future Returns in Sweden?

4.2.1 Univariate Portfolio Analysis

Table 5 (Page 21) shows the univariate portfolio sort across both the 12-month and 24-month estimation window in which we present both equally weighted portfolios and value weighted portfolios as well as quintile and decile sorts.

Across most specifications, the High-Low spread is negative, which is consistent with a negative relation between RA and future stock returns in Sweden. The strongest evidence appears in the 12-month equal weighted portfolios. In Panel A, the quintile High-Low spread is -0.609 for average returns, with similarly negative and statistically significant spreads for the CAPM, FF3, and Carhart alphas. In Panel B, the decile sorts point in the same direction. The average next-month excess return spread is -0.542 percentage points, while the FF3 and Carhart spreads are -0.792 and -0.796, percentage points respectively. These results indicate that low-RA stocks tend to outperform high-RA stocks, especially when RA is measured over the 12-month window and the full cross-section is given equal weight.

The 24-month results are weaker. Under equal weighting, the quintile spreads remain negative, but significance is concentrated in the FF3 and Carhart alphas rather than in raw returns or the CAPM alpha. The same pattern appears in the decile sorts, where the spreads remain negative but are generally less precisely estimated. This suggests that extending the estimation window does not strengthen the pricing signal in the Swedish sample. One possible explanation is that the longer window produces a smoother measure of asymmetry but also incorporates older information that is less relevant for next-month returns.

The value weighted results are weak throughout. In the 12-month quintile sorts, the average next-month excess return spread is only -0.183 percentage points, and the corresponding FF3 and Carhart spreads are also insignificant. The 24-month value weighted results are similarly weak. This suggests that the RA effect is concentrated outside the largest firms in the Swedish market. This is consistent with the earlier descriptive evidence (Table 2 and 3), which shows that high-RA stocks are on average larger, but also less volatile and less illiquid than low-RA stocks. High RA in Sweden therefore differs from the conventional profile of small, highly speculative lottery-type firms. In a small and concentrated market such as Sweden, where a limited number of firms can dominate value weighted returns, the weak value weighted results suggest that the asymmetry effect is mainly a feature of the broader cross-section rather than of the largest and most investable stocks.

4.2.2 Bivariate Portfolio Sorts

Table 6 (Page 23) reports dependent bivariate portfolio sorts. The reported High-Low row shows the difference in the RA spread between the highest and lowest characteristic quintiles. The results are negative for all control characteristics and statistically significant in most cases. The strongest effects appear for IVOL and ILLIQ, where the High- Low spreads are -0.733 and -0.620 percentage points respectively. This suggests that the predictive content of RA is not absorbed by standard firm characteristics and is especially strong in stocks with higher idiosyncratic volatility and lower liquidity.

While the coefficient remains negative for the bivariate sort on ISKEW, it is not statistically significant, which suggests that the RA spread is not materially stronger in either low- or high-ISKEW stocks. Thus, the bivariate sort provides no evidence that the RA effect differs systematically across idiosyncratic skewness groups. At the same time, the negative sign indicates that RA and ISKEW are not equivalent. Rather, the result suggests that the overlap between the two measures is greater than for the other controls.

Table 5: Univariate Portfolio Sort of RA

Table 5: This table reports next-month excess returns in percentage points for portfolios sorted on RA. At the end of each month, stocks are sorted into portfolios based on RA estimated from daily residuals over either a 12-month or 24-month estimation window. Panel A reports results for RA-sorted quintile portfolios, while Panel B reports results for RA-sorted decile portfolios. For each specification, the table presents equal weighted and value weighted average excess returns as well as CAPM alphas, Fama-French three-factor alphas and Carhart four-factor alphas. **Low** denotes the portfolio with the lowest RA, and High denotes the portfolio with the highest RA. The High-Low row reports the return spread between the highest-RA and lowest-RA portfolios. Newey-West t-statistics are reported in parentheses. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Panel A: Quintile Portfolio Sorts

	12-month estimation period								24-month estimation period							
	Equal weighted				Value weighted				Equal weighted				Value weighted			
	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha
Low	1.539***	1.397***	1.451***	2.032***	0.991**	0.882**	1.014***	1.432***	1.501***	1.378***	1.485***	2.090***	1.060***	0.950***	1.061***	1.340***
	(3.27)	(3.12)	(3.37)	(5.08)	(2.43)	(2.31)	(2.82)	(3.81)	(3.16)	(2.95)	(3.22)	(4.92)	(2.94)	(2.78)	(2.90)	(3.56)
2	1.019**	0.872**	0.808**	1.508***	0.845**	0.793*	0.876**	1.363***	1.011**	0.842**	0.816**	1.453***	0.948***	0.911***	0.926***	1.354***
	(2.24)	(2.04)	(1.96)	(3.74)	(2.07)	(1.90)	(2.13)	(3.09)	(2.21)	(2.01)	(2.04)	(3.58)	(2.74)	(2.60)	(2.65)	(3.51)
3	1.128***	1.008**	0.965**	1.497***	0.795**	0.750**	0.882**	1.259***	1.012**	0.879**	0.798*	1.353***	0.584	0.487	0.726*	1.274***
	(2.73)	(2.55)	(2.35)	(3.91)	(2.12)	(1.98)	(2.14)	(3.14)	(2.39)	(2.19)	(1.93)	(3.53)	(1.39)	(1.17)	(1.73)	(3.10)
4	1.104***	0.979**	0.876**	1.413***	0.336	0.264	0.464	0.919***	1.093***	0.987***	0.887**	1.411***	0.765**	0.723*	0.884**	1.439***
	(2.75)	(2.57)	(2.21)	(3.69)	(0.93)	(0.72)	(1.24)	(2.64)	(2.75)	(2.61)	(2.35)	(3.88)	(2.06)	(1.90)	(2.37)	(4.04)
High	0.930**	0.822**	0.713*	1.278***	0.808**	0.770**	0.831**	1.290***	1.105***	0.995***	0.826**	1.423***	0.819***	0.795**	0.819**	1.186***
	(2.31)	(2.17)	(1.93)	(3.57)	(2.55)	(2.40)	(2.57)	(4.02)	(2.73)	(2.59)	(2.21)	(3.96)	(2.60)	(2.47)	(2.47)	(3.62)
High-Low	**-0.609*** **	**-0.575*** **	**-0.738*** **	**-0.754*** **	**-0.183**	**-0.112**	**-0.183**	**-0.142**	**-0.396**	**-0.384**	**-0.659** **	**-0.667*** **	**-0.242**	**-0.155**	**-0.242**	**-0.153**
	(-3.11)	**(-2.80)**	**(-3.69)**	**(-3.93)**	**(-0.70)**	**(-0.41)**	**(-0.63)**	**(-0.47)**	**(-1.49)**	**(-1.39)**	**(-2.55)**	**(-2.70)**	**(-1.15)**	**(-0.71)**	**(-1.08)**	**(-0.60)**

Panel B: Decile Portfolio Sorts

	12-month estimation period								24-month estimation period							
	Equal weighted				Value weighted				Equal weighted				Value weighted			
	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha
Low	1.552***	1.455***	1.563***	2.117***	0.949**	0.808**	0.916**	1.294***	1.438***	1.268***	1.405***	2.122***	1.474***	1.305***	1.281***	1.633***
	(3.28)	(2.93)	(3.26)	(4.81)	(2.19)	(2.02)	(2.25)	(3.10)	(2.74)	(2.62)	(2.99)	(4.57)	(3.32)	(3.22)	(2.87)	(3.68)
2	1.523***	1.336***	1.333***	1.943***	1.246***	1.152***	1.255***	1.682***	1.568***	1.494***	1.571***	2.061***	0.944***	0.867**	1.048***	1.278***
	(2.86)	(2.79)	(2.90)	(4.52)	(2.81)	(2.76)	(3.36)	(4.26)	(3.07)	(2.72)	(2.79)	(4.17)	(2.66)	(2.49)	(2.81)	(3.38)
3	1.179**	1.040**	0.990**	1.766***	0.798*	0.668*	0.749*	1.135***	1.078**	0.925**	0.880**	1.520***	0.608	0.541	0.484	0.942**
	(2.51)	(2.28)	(2.26)	(3.90)	(1.93)	(1.69)	(1.86)	(2.76)	(2.33)	(2.15)	(2.16)	(3.55)	(1.53)	(1.37)	(1.20)	(2.07)
4	0.859*	0.704	0.626	1.250***	0.893**	0.873*	0.868*	1.374***	0.944*	0.760*	0.753*	1.386***	1.219***	1.160***	1.232***	1.599***
	(1.83)	(1.62)	(1.49)	(3.16)	(2.01)	(1.90)	(1.96)	(2.87)	(1.95)	(1.72)	(1.78)	(3.32)	(3.14)	(3.00)	(3.23)	(4.05)
5	1.068**	0.929**	0.902**	1.384***	1.007**	0.888*	1.065**	1.424***	1.039**	0.926**	0.902**	1.399***	0.718	0.596	0.886*	1.266***
	(2.44)	(2.24)	(2.08)	(3.51)	(2.08)	(1.94)	(2.15)	(2.77)	(2.44)	(2.23)	(2.05)	(3.49)	(1.63)	(1.35)	(1.94)	(2.78)
6	1.187***	1.086***	1.027**	1.608***	0.707*	0.657*	0.808*	1.185***	0.985**	0.832**	0.694*	1.309***	0.642	0.564	0.612	1.205***
	(2.80)	(2.64)	(2.42)	(3.86)	(1.84)	(1.68)	(1.89)	(2.76)	(2.19)	(2.00)	(1.67)	(3.26)	(1.44)	(1.24)	(1.40)	(2.76)
7	1.023**	0.901**	0.789**	1.368***	0.619	0.561	0.691	1.111**	1.089**	0.974**	0.838**	1.434***	0.791*	0.684*	0.681*	1.223***
	(2.42)	(2.24)	(1.96)	(3.51)	(1.57)	(1.36)	(1.53)	(2.38)	(2.51)	(2.37)	(2.11)	(3.75)	(1.87)	(1.67)	(1.79)	(3.24)
8	1.186***	1.060***	0.964**	1.463***	0.199	0.088	0.349	0.839**	1.094***	0.998***	0.933**	1.386***	0.913**	0.905**	1.164***	1.732***
	(2.86)	(2.63)	(2.22)	(3.43)	(0.47)	(0.20)	(0.82)	(2.29)	(2.83)	(2.65)	(2.39)	(3.66)	(2.33)	(2.16)	(2.64)	(3.77)
9	0.848**	0.730*	0.653*	1.234***	0.992***	0.985***	0.947***	1.377***	0.901**	0.805**	0.656*	1.209***	0.675*	0.586	0.610*	1.001***
	(2.03)	(1.89)	(1.79)	(3.42)	(2.94)	(2.83)	(2.85)	(4.08)	(2.37)	(2.19)	(1.79)	(3.27)	(1.81)	(1.61)	(1.70)	(2.75)
High	1.010**	0.913**	0.771*	1.322***	0.610	0.520	0.696*	1.317***	1.309***	1.185***	0.996**	1.638***	0.991***	0.993***	0.993***	1.506***
	(2.46)	(2.30)	(1.96)	(3.50)	(1.56)	(1.36)	(1.86)	(3.64)	(2.86)	(2.76)	(2.45)	(4.25)	(2.78)	(2.64)	(2.72)	(4.16)
High-Low	**-0.542***	**-0.543**	**-0.792** **	**-0.796*** **	**-0.338**	**-0.288**	**-0.220**	**0.023**	**-0.129**	**-0.083**	**-0.409**	**-0.484**	**-0.483**	**-0.312**	**-0.288**	**-0.127**
	(-1.82)	**(-1.64)**	**(-2.56)**	**(-2.78)**	**(-1.03)**	**(-0.84)**	**(-0.60)**	**(0.06)**	**(-0.39)**	**(-0.25)**	**(-1.54)**	**(-1.53)**	**(-1.55)**	**(-1.00)**	**(-0.93)**	**(-0.40)**

4.2.3 Fama-MacBeth Regressions

Next, we run Fama-MacBeth regressions shown in Table 7 (Page 23). The Fama-MacBeth regressions indicate similar results to the bivariate portfolio evidence in Table 6. The coefficient on RA is negative in every specification and remains statistically significant even after the full set of control variables is included. At the same time, both the magnitude and the statistical significance of the coefficient weaken as additional controls are added. In the univariate specification, the coefficient on RA is -12.121 percentage points and significant at the 1% level. In the full specification, it declines to -7.519 percentage points and remains significant at the 10% level. This suggests that some of the information in RA overlaps with standard firm characteristics, but not enough to eliminate its predictive content. The regressions therefore support the earlier evidence from the bivariate portfolio sorts that the RA effect is not fully absorbed by the control variables.

Table 7 also helps clarify the relation between RA and conventional idiosyncratic skewness. In the bivariate sorts (Table 6), the ISKEW High-Low spread was negative but insignificant, which made it less clear whether the two measures were distinct or just overlapping. Here, the answer is more direct. Once RA is included, the coefficient on ISKEW is small and statistically insignificant across all specifications. We therefore interpret Table 7 as stronger evidence that conventional idiosyncratic skewness does not contain independent explanatory power for future returns beyond what is already captured by RA. In that sense, the regressions strengthen the view that the density-based measure captures the relevant aspect of return asymmetry more effectively than traditional third moment skewness.

Table 6: Bivariate Portfolio Sort Quintiles

Table 6: This table reports the results from dependent bivariate portfolio sorts on RA and firm characteristics. At the end of each month, stocks are first sorted into quintiles based on the indicated characteristic (MV, BM, MOM, BETA, TURN, ILLIQ, IVOL, ISKEW, COSKEW, MAX, MIN and REV). Within each characteristic quintile, stocks are then sorted into RA quintiles. The reported values correspond to the next-month excess return spread in percentage points between the highest-RA and lowest-RA portfolios within each characteristic quintile, with Newey-West t-statistics reported in parentheses. Low and High denote the lowest and highest quintiles of the control characteristic, respectively. The High-Low row reports the difference in the RA spread between the highest and lowest characteristic quintiles. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

	MV	BM	MOM	BETA	TURN	ILLIQ	IVOL	ISKEW	COSKEW	MAX	MIN	REV
Low	1.247***	1.331***	1.387***	1.424***	1.372***	1.529***	1.577***	1.359***	1.358***	1.527***	1.448***	1.395***
	(2.81)	(2.80)	(3.00)	(3.15)	(2.94)	(3.33)	(3.64)	(3.16)	(2.98)	(3.47)	(3.32)	(3.13)
2	1.091**	1.235***	1.123**	1.182***	1.051**	0.939**	1.069**	1.202***	1.148**	1.198***	1.150***	1.153***
	(2.47)	(2.67)	(2.52)	(2.73)	(2.28)	(2.18)	(2.42)	(2.70)	(2.55)	(2.75)	(2.59)	(2.59)
3	1.121***	1.034**	1.061***	1.110***	1.121***	1.157***	1.151***	0.835*	1.182***	1.126***	1.107***	1.060**
	(2.59)	(2.44)	(2.62)	(2.61)	(2.61)	(2.75)	(2.62)	(1.89)	(2.78)	(2.64)	(2.59)	(2.49)
4	1.193***	1.177***	1.185***	1.035**	0.939**	1.069**	1.065**	1.167***	0.961**	0.958**	1.063**	1.090***
	(2.88)	(2.89)	(2.84)	(2.55)	(2.33)	(2.54)	(2.56)	(2.84)	(2.44)	(2.32)	(2.57)	(2.70)
High	1.010**	0.881**	0.914**	0.918**	1.058***	0.909**	0.844**	1.100***	1.021**	0.856**	0.899**	0.961**
	(2.47)	(2.21)	(2.31)	(2.24)	(2.59)	(2.18)	(2.06)	(2.75)	(2.55)	(2.08)	(2.21)	(2.40)
High-Low	**-0.237***	**-0.450****	**-0.473****	**-0.506*****	**-0.313***	**-0.620*****	**-0.733*****	**-0.259**	**-0.337***	**-0.671*****	**-0.550*****	**-0.433****
	(-1.66)	(-2.53)	(-2.51)	(-3.06)	(-1.86)	(-3.42)	(-4.30)	(-1.58)	(-1.76)	(-3.81)	(-3.36)	(-2.55)

Table 7: Fama-MacBeth regressions

Table 7: This table reports the monthly Fama-MacBeth cross-sectional regressions of next month excess stock returns on RA and a set of firm characteristics. The estimated monthly cross-sectional regression is $R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}$. Where $X_{i,t}$ is a vector of controlled variables defined below. R1-R12 present alternative model specifications with an increasingly rich set of control variables. The dependent variable is next-month excess return, and the results are in percentage point units. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV firm size logged, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity (for readability ILLIQ is scaled by 10^6), COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics in parentheses. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
ISKEW		0.075	0.151	0.024	0.040	-0.039	0.000	0.001	0.000	-0.005	-0.004	-0.014
		(0.74)	(1.60)	(0.36)	(0.61)	(-0.62)	(0.01)	(0.02)	(0.01)	(-0.07)	(-0.05)	(-0.22)
RA	-12.121***	-9.981**	-12.269***	-10.701***	-11.494***	-6.969*	-7.694**	-7.734**	-7.652**	-7.807**	-7.260*	-7.519*
	(-2.75)	(-2.54)	(-3.33)	(-2.67)	(-2.97)	(-1.77)	(-2.11)	(-2.12)	(-2.08)	(-2.03)	(-1.86)	(-1.84)
IVOL			-26.573***	-35.364***	-31.401***	-27.348***	-22.285***	-23.294***	-23.634***	-22.818***	-38.452***	-45.450**
			(-3.26)	(-4.21)	(-3.97)	(-3.61)	(-3.13)	(-3.28)	(-3.18)	(-3.08)	(-3.46)	(-2.42)
MV				-0.160***	-0.123***	-0.163***	-0.071	-0.081	-0.078	-0.074	-0.076	-0.099*
				(-4.08)	(-2.90)	(-3.91)	(-1.18)	(-1.32)	(-1.23)	(-1.19)	(-1.25)	(-1.67)
BM					0.176**	0.161**	0.142**	0.186**	0.188**	0.194***	0.193***	0.178**
					(2.34)	(2.25)	(2.05)	(2.57)	(2.54)	(2.62)	(2.60)	(2.46)
MOM						1.435***	1.222***	1.268***	1.246***	1.277***	1.306***	1.349***
						(3.08)	(2.89)	(3.01)	(2.98)	(3.03)	(3.14)	(3.03)
BETA							-0.947**	-0.893**	-0.827**	-0.800*	-0.799*	-0.913**
							(-2.38)	(-2.22)	(-2.04)	(-1.90)	(-1.84)	(-2.13)
TURN								-11.924**	-13.946**	-13.604**	-13.425**	-14.442**
								(-2.00)	(-2.27)	(-2.21)	(-2.22)	(-2.37)
ILLIQ									0.148	0.146	0.157	0.145
									(1.37)	(1.36)	(1.43)	(1.37)
COSKEW										-0.158	-0.169	0.151
										(-0.23)	(-0.25)	(0.22)
MAX											5.050	5.677
											(1.37)	(1.31)
MIN												2.587
												(0.49)
REV												1.966**
												(2.37)
Intercept	1.023**	0.983**	1.532***	3.013***	2.696***	2.790***	2.610***	2.714***	2.658***	2.615***	2.706***	2.889***
	(2.55)	(2.47)	(4.28)	(5.85)	(5.10)	(5.30)	(4.76)	(4.84)	(4.58)	(4.50)	(4.76)	(5.12)

4.3 When Is the RA Effect Stronger? Evidence from Market Regimes

Previous results have indicated that the RA effect is present in the Swedish stock market and does reliably predict future returns. A natural next step is to understand where the RA effect might appear stronger by looking at different states and regimes.

4.3.1 RA Heterogeneity

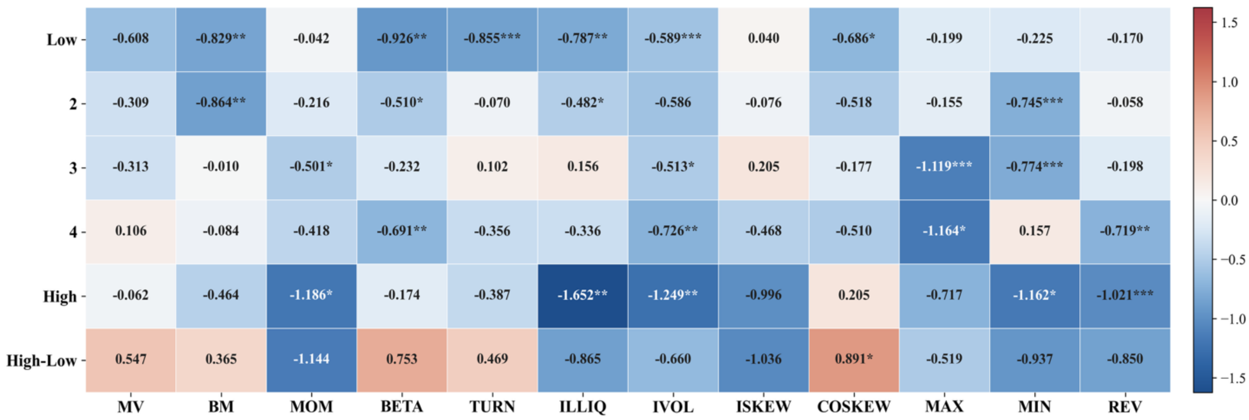

Figure 1: Heterogeneity test using Dependent Bivariate sort method

Note: This figure presents a bivariate sort on key control characteristics defined as followed: RA is the residual-based measure of return asymmetry; MV is firm size reported in logged terms; BM is book-to-market reported in logged terms; MOM is momentum; BETA is the market beta; TURN is turnover; ISKEW is idiosyncratic skewness; IVOL is idiosyncratic volatility; ILLIQ is the Amihud illiquidity measure; COSKEW is coskewness; MAX and MIN are the maximum and minimum daily returns within the month; and REV is short-term reversal. Stocks are first sorted based on control characteristic then, for each control quintile, the return spread between the highest-RA portfolio and the lowest-RA portfolio is calculated using next-month excess returns. This procedure yields one RA spread for each control-characteristic quintile. The reported values are percentage point spread difference between high-RA and low-RA stocks within each control characteristic. Newey-West t-statistics in parentheses. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Figure 1 presents the same dependent bivariate sort framework as in Section 4.2.2 but reports the RA spread separately within each control-characteristic quintile rather than focusing only on the High-Low difference across quintiles. This presentation makes the cross-sectional heterogeneity in the RA effect easier to see. More negative cells (blue) indicate that high-RA stocks underperform low-RA stocks within that characteristic quintile, while positive cells (red) indicate the opposite.

Figure 1 shows that the RA effect is not equally strong across all parts of the cross-section. The clearest heterogeneity appears for variables related to trading frictions. For ILLIQ, the spread becomes much more negative in the highest illiquidity quintile than in the lowest quintile (-1.652 versus -0.787 percentage points). A similar pattern appears for IVOL, where the spread is more negative in the highest-volatility quintile than in the lowest (-1.249 versus -0.589 percentage points). These results suggest that the RA effect is stronger where limits to arbitrage are more severe.

A similar, although less uniform, pattern appears across size and valuation groups. For MV, the spread is more negative in the Low-MV quintile than in the High-MV quintile (-0.608 versus -0.062 percentage points), which suggests that the effect is stronger among smaller stocks. For BM, the strongest negative spreads appear in the Low-BM quintiles, especially the first two groups (-0.829 and -0.864 percentage points), which points to a stronger effect among growth-oriented stocks than among value stocks.

The pattern is less clear for some of the other characteristics. For example, COSKEW does not display a monotonic pattern across quintiles, even though the High-Low difference is significant. Several other controls also show mixed intermediate values. Figure 1 therefore provides no indication that every control characteristic generates a clear gradient in the RA spread. Instead, the strongest and most consistent heterogeneity appears for illiquidity, idiosyncratic volatility, firm size, and book-to-market.

4.3.2 Liquidity Regimes

Table 8: Liquidity and RA

Table 8: This table reports the results for the liquidity regime analysis. Panel A presents monthly Fama-MacBeth cross-sectional regressions of next-month excess returns estimated separately in high- and low-liquidity regimes, where the regimes are defined by splitting the sample at the mean value of aggregate market liquidity (ALIQ). The estimated monthly cross-sectional regression $R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \beta_{ISKEW,t} ISKEW_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}$ where $X_{i,t}$ is a vector of controlled variables defined below. The six specifications are defined as follows: Specification (1) includes ISKEW only; Specification (2) includes RA only; Specification (3) includes both RA and ISKEW; Specification (4) includes ISKEW and the full set of control variables; Specification (5) includes RA and the full set of control variables; and Specification (6) includes RA, ISKEW, and the full set of control variables. The dependent variable is next-month excess return reported in percentage points. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV logged firm size, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity, COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month, and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics in parentheses. Panel B reports dependent bivariate portfolio sorts in which stocks are first sorted into quintiles based on ILLIQ and then into RA quintiles within each illiquidity group. RA(5-1) denotes the one-month-ahead excess return spread between the highest-RA and lowest-RA portfolios within each ILLIQ quintile. Newey-West t-statistics are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Panel A: Fama-MacBeth Regressions on RA and Liquidity Regimes

	High Liquidity Regime						Low Liquidity Regime					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ISKEW	0.223*		0.207	-0.027		-0.019	-0.140		-0.191	0.053		-0.004
	(1.72)		(1.59)	(-0.37)		(-0.25)	(-1.01)		(-1.33)	(0.37)		(-0.03)
RA		-10.262**	-5.482		1.967	1.590		-14.999*	-18.044**		-27.198***	-27.146***
		(-2.24)	(-1.47)		(0.51)	(0.40)		(-1.95)	(-2.30)		(-3.70)	(-3.74)
IVOL				-23.309	-22.811	-23.310				-90.691***	-94.161***	-93.155***
				(-1.02)	(-0.98)	(-1.01)				(-3.05)	(-3.16)	(-3.12)
MV				-0.178***	-0.179***	-0.181***				0.053	0.086	0.077
				(-2.71)	(-2.64)	(-2.76)				(0.52)	(0.90)	(0.79)
BM				0.090	0.088	0.086				0.344*	0.382**	0.377**
				(1.30)	(1.26)	(1.24)				(1.92)	(2.23)	(2.15)
MOM				1.737***	1.711***	1.749***				0.750	0.350	0.485
				(5.03)	(5.02)	(5.03)				(0.64)	(0.30)	(0.41)
BETA				-0.482	-0.459	-0.450				-1.698**	-1.981**	-1.909**
				(-1.08)	(-1.04)	(-1.02)				(-2.12)	(-2.52)	(-2.40)
TURN				-16.556***	-16.214***	-16.294***				-8.153	-8.457	-10.450
				(-2.91)	(-2.96)	(-2.90)				(-0.51)	(-0.55)	(-0.66)
ILLIQ				0.212	0.198	0.207				0.013	0.012	0.012
				(1.35)	(1.28)	(1.35)				(1.49)	(1.26)	(1.27)
COSKEW				-0.735	-0.823	-0.756				1.778	2.186	2.107
				(-1.13)	(-1.25)	(-1.16)				(1.19)	(1.44)	(1.38)
MAX				2.846	2.428	3.063				11.474	11.111	11.309
				(0.58)	(0.48)	(0.62)				(1.43)	(1.35)	(1.39)
MIN				-6.076	-5.631	-6.176				20.526**	22.202**	21.468**
				(-0.97)	(-0.91)	(-0.97)				(2.13)	(2.33)	(2.24)
REV				3.570***	3.398***	3.531***				-1.072	-1.681	-1.405
				(3.97)	(3.82)	(3.90)				(-0.71)	(-1.04)	(-0.90)
Intercept	1.253***	1.290***	1.205***	3.528***	3.503***	3.529***	0.647	0.453	0.512	1.760**	1.489*	1.510*
	(3.14)	(3.23)	(3.08)	(5.64)	(5.52)	(5.67)	(0.71)	(0.51)	(0.57)	(1.97)	(1.81)	(1.77)

Panel B: Bivariate Portfolio Sorts on Illiquidity and RA

ILLIQ quintile	RA1	RA2	RA3	RA4	RA5	RA(5-1)
ILLIQ1	1.810***	1.241***	1.097***	1.441***	1.033***	-0.777**
	(3.65)	(3.45)	(2.90)	(2.80)	(2.98)	(-2.22)
ILLIQ2	1.692***	1.010**	1.091***	1.212**	1.183***	-0.509**
	(3.72)	(2.10)	(2.82)	(2.57)	(2.85)	(-2.03)

ILLIQ3	1.122**	1.170**	1.280**	1.497***	1.257***	0.135
	(2.14)	(2.39)	(2.55)	(3.39)	(2.60)	(0.40)
ILLIQ4	1.124*	0.917**	1.139**	0.814*	0.751	-0.373
	(1.85)	(1.96)	(2.37)	(1.66)	(1.49)	(-1.09)
ILLIQ5	2.010***	0.413	1.181*	0.401	0.357	-1.654**
	(2.72)	(0.62)	(1.66)	(0.68)	(0.65)	(-2.56)

Table 8 examines whether the RA effect varies across liquidity regimes. Panel A reports Fama-MacBeth regressions for high- and low-liquidity states, where liquidity is measured using aggregate market liquidity and the sample is split at the mean of ALIQ (See Table 1 for equation specifications). Panel B reports the bivariate portfolio sort on illiquidity (ILLIQ).

Observing Panel A, we can see that RA is state dependent, especially in low-liquidity regimes. The coefficient stays large and statistically significant for all four RA specifications while in the high-liquidity regime, the coefficient is only statistically significant under specification (2) and shrinks towards zero as more controls are added in later specifications.

Moreover, in the low-liquidity regime, ISKEW is positive and weakly significant only in the univariate specification. Once RA and the other controls are added, it becomes insignificant. In the high-liquidity state, ISKEW is negative but insignificant throughout. This suggests that conventional idiosyncratic skewness does not display a stable relation with future returns across liquidity states, especially compared with RA.

Panel B reports dependent bivariate portfolio sorts in which stocks are first sorted into illiquidity quintiles and then into RA quintiles within each group with the main results presented in column RA (5-1). The reported RA (5-1) spread is negative in four of the five illiquidity quintiles and statistically significant in the first, second, and fifth quintiles. The strongest spread appears in the highest-illiquidity quintile, where the RA (5-1) spread is -1.654. By comparison, the spreads in the lowest and second-lowest illiquidity quintiles are -0.777 and -0.509 respectively, while the middle quintiles show weaker and less consistent results. These portfolio results suggest that the negative RA-return relation extends beyond illiquid stocks, but is strongest where illiquidity is greatest. Panel B therefore reinforces the evidence from Panel A that the RA effect becomes more pronounced when market liquidity is poor.

4.3.3 Volatility Regimes

Table 9: Volatility Regimes and RA

Table 9: This table reports the results for the volatility regime analysis. Panel A presents monthly Fama-MacBeth cross-sectional regressions of next-month excess returns estimated separately in high- and low-volatility regimes, where the regimes are defined by splitting the sample at the mean value of aggregate market volatility (ARSMV). The estimated monthly cross-sectional regression $R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \beta_{ISKEW,t} ISKEW_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}$ where $X_{i,t}$ is a vector of controlled variables defined below. Specification (1) includes ISKEW only, (2) includes RA only, (3) includes both RA and ISKEW, (4) includes ISKEW and the control variables, (5) includes RA and the control variables, and (6) includes RA, ISKEW, and the control variables. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV logged firm size, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity, COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month, and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics in parentheses. Panel B reports dependent bivariate portfolio sorts in which stocks are first sorted into quintiles based on IVOL and then into RA quintiles within each volatility group. RA (5-1) denotes the one-month-ahead excess return spread between the highest-RA and lowest-RA portfolios within each IVOL quintile. Newey-West t-statistics are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Panel A: Fama-MacBeth Regressions on RA and Volatility Regimes

	High Volatility Regime						Low Volatility Regime					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)

ISKEW	0.226		0.197	0.085		0.047	0.032		0.003	-0.052		-0.050
	(1.07)		(0.93)	(1.00)		(0.53)	(0.32)		(0.03)	(-0.57)		(-0.55)
RA		-15.556**	-9.826		-16.386**	-15.709**		-10.085*	-10.074**		-1.933	-2.713
		(-2.02)	(-1.58)		(-2.19)	(-2.06)		(-1.91)	(-1.96)		(-0.44)	(-0.62)
IVOL				-72.927***	-78.439***	-74.978***				-28.085	-26.056	-28.122
				(-3.21)	(-3.32)	(-3.20)				(-1.04)	(-0.97)	(-1.04)
MV				-0.082	-0.079	-0.073				-0.118	-0.105	-0.115
				(-1.02)	(-0.97)	(-0.92)				(-1.51)	(-1.36)	(-1.48)
BM				0.092	0.110	0.109				0.217***	0.223***	0.219***
				(0.70)	(0.86)	(0.85)				(2.70)	(2.84)	(2.73)
MOM				0.086	-0.078	-0.069				2.210***	2.077***	2.181***
				(0.09)	(-0.08)	(-0.07)				(5.66)	(5.58)	(5.60)
BETA				-0.760	-0.890	-0.878				-0.930*	-0.971*	-0.933*
				(-0.97)	(-1.11)	(-1.10)				(-1.83)	(-1.93)	(-1.85)
TURN				-16.218*	-17.416**	-17.098*				-12.528	-11.607	-12.883
				(-1.83)	(-1.99)	(-1.94)				(-1.54)	(-1.46)	(-1.58)
ILLIQ				0.194	0.202	0.192				0.123	0.102	0.117
				(0.89)	(0.92)	(0.88)				(0.93)	(0.81)	(0.93)
COSKEW				0.729	0.955	0.881				-0.331	-0.352	-0.277
				(0.75)	(0.93)	(0.87)				(-0.36)	(-0.38)	(-0.30)
MAX				5.321	5.862	5.149				5.733	4.781	5.986
				(0.85)	(0.92)	(0.82)				(0.96)	(0.78)	(1.00)
MIN				18.628***	20.201***	19.518***				-7.193	-6.790	-7.349
				(2.81)	(2.94)	(2.86)				(-0.99)	(-0.96)	(-1.01)
REV				1.380	1.261	1.199				2.521**	2.097**	2.417**
				(1.07)	(0.94)	(0.91)				(2.47)	(2.02)	(2.32)
Intercept	0.599	0.578	0.518	2.122**	2.093**	2.011**	1.334***	1.288***	1.259***	3.464***	3.317***	3.405***
	(0.75)	(0.75)	(0.66)	(2.33)	(2.30)	(2.25)	(3.33)	(3.12)	(3.19)	(5.35)	(5.24)	(5.30)

Panel B: Bivariate Portfolio Sorts on Volatility and RA

IVOL quintile	RA1	RA2	RA3	RA4	RA5	RA(5-1)
IVOL1	1.727***	1.205***	1.608***	1.697***	1.138***	-0.589***
	(4.87)	(3.43)	(4.14)	(3.41)	(3.37)	(-3.29)
IVOL2	1.842***	1.175***	1.202***	1.117***	1.256***	-0.586
	(3.53)	(3.07)	(2.91)	(2.90)	(3.30)	(-1.48)
IVOL3	1.471***	1.272**	1.589***	1.020**	0.958**	-0.513*
	(2.98)	(2.57)	(3.37)	(2.37)	(2.05)	(-1.71)
IVOL4	1.392**	0.930*	1.260*	1.038*	0.666	-0.726**
	(2.42)	(1.69)	(1.95)	(1.87)	(1.28)	(-2.16)
IVOL5	1.452**	0.763	0.098	0.454	0.202	-1.249**
	(2.00)	(1.06)	(0.15)	(0.78)	(0.36)	(-1.98)

Table 9 examines whether the RA effect varies with volatility. Aggregate market volatility is measured by $ARSMV_t$, defined as the monthly standard deviation of daily market excess returns (See Table 1 for equation specification). Panel A compares Fama-MacBeth estimates across low and high volatility regimes, while Panel B reports RA-sorted portfolio spreads across idiosyncratic volatility quintiles in the full sample.

Panel A shows that the RA effect differs across volatility states. In low-volatility periods, the coefficient on RA is negative, but it is not statistically significant in the fuller specifications. In high-volatility periods, by contrast, the coefficient is more negative and remains significant both when RA is entered alone and when the full set of controls are included. This suggests that the negative RA-return relation is more visible in periods of high aggregate volatility.

Panel B shows that the RA effect is concentrated at the tails of the idiosyncratic volatility distribution rather than spread evenly across it. The negative RA (5-1) spread is statistically significant in the lowest-IVOL quintile, disappears in the middle of the distribution and then becomes largest in the highest-IVOL quintile, where it reaches -1.111 percentage points. This suggests that the negative RA-return relation is strongest where firm-level volatility is highest as arbitrage is more difficult and the negative relation between RA and future returns becomes more visible. At the same time, the significant spread in the lowest-IVOL quintile shows that the RA effect is not confined to highly speculative stocks. Overall, Table 9 suggests that volatility provides some support for the limits-to-arbitrage interpretation, although the pattern is less clean than in the liquidity results.

4.3.4 Arbitrage Frictions

Table 10: Arbitrage Index and RA

Table 10: This table reports dependent portfolio sorts on residual asymmetry (RA) and an arbitrage-friction index using equal weighted quintile portfolios. At the end of each month, stocks are first assigned decile ranks based on idiosyncratic volatility (IVOL) and illiquidity (ILLIQ). The arbitrage index is then constructed as the sum of these two decile ranks, such that higher values indicate stocks that are more difficult to arbitrage. Stocks are next sorted into quintiles based on the arbitrage index and then into RA quintiles within each arbitrage-friction group. Arb1 denotes the lowest-arbitrage-friction quintile and Arb5 the highest-arbitrage-friction quintile. Within each arbitrage-friction quintile, RA1 denotes the portfolio with the lowest RA and RA5 the portfolio with the highest RA. The reported values are next-month excess returns in percentage points. The RA(5-1) column reports the one-month-ahead excess return spread between the highest-RA and lowest-RA portfolios within each arbitrage-friction quintile. Newey-West t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas and Riksbanken.

Arbitrage quintile	RA1	RA2	RA3	RA4	RA5	RA(5-1)
Arb1	1.408***	1.436***	1.243***	1.363***	1.224***	-0.184
	(4.14)	(3.72)	(3.42)	(3.31)	(3.59)	(-1.11)
Arb2	2.293***	1.446***	1.296***	1.467***	1.100***	-1.194**
	(3.48)	(3.20)	(3.42)	(3.62)	(3.00)	(-2.25)
Arb3	1.555***	1.137**	1.061**	1.249**	1.279**	-0.276
	(2.99)	(2.41)	(2.02)	(2.55)	(2.54)	(-0.79)
Arb4	1.216**	0.942*	1.004**	0.607	0.432	-0.784**
	(2.01)	(1.73)	(1.97)	(1.12)	(0.78)	(-2.20)
Arb5	1.436**	0.354	0.952	0.308	-0.226	-1.663***
	(2.12)	(0.56)	(1.35)	(0.45)	(-0.34)	(-2.79)

Table 10 reports the joint sort on RA and arbitrage costs using equal weighted quintile portfolios. To understand whether the predictive effect of RA varies with arbitrage frictions, we construct an arbitrage index based on idiosyncratic volatility and illiquidity. Each month, stocks are ranked into deciles by $IVOL$ and $ILLIQ$ (See Table 1). The arbitrage index is defined as the sum of the two decile ranks, so that higher values indicate stocks that are more difficult to arbitrage.

The key findings are in the RA (5-1), which is the return difference between the highest-RA and lowest-RA portfolios within each arbitrage-friction quintile. The table shows that the spread is small and insignificant in the lowest-friction group at -0.184 percentage points but becomes more negative and statistically significant in the higher-friction groups, with the strongest effect observed in Arb5 of -1.663 percentage points. Although the pattern is not perfectly monotonic across all quintiles, the overall evidence suggests that the negative RA-return relation is concentrated among stocks facing the greatest limits to arbitrage. The evidence therefore points to a stronger RA effect in the high-arbitrage-cost segment rather than to a uniform increase across all levels of arbitrage costs.

4.3.5 Economic Policy Uncertainty

Table 11: Swedish EPU effect of RA on 3-months holding periods

Table 11: This table reports monthly Fama-MacBeth cross-sectional regressions of three-month cumulative excess stock returns estimated separately in high- and low-Swedish-EPU regimes, where the regimes are defined by splitting the sample at the mean value of the Swedish Economic Policy Uncertainty (EPU) index. The estimated monthly cross-sectional regression is $R^{e,(3)}_{i,t+1:t+3} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1:t+3}$ where $X_{i,t}$ is a vector of controlled variables defined below the dependent variable is defined as the cumulative excess return over 3 months, is $R^{e,(3)}_{i,t+1:t+3} = (1 + R^{e}_{i,t+1})(1 + R^{e}_{i,t+2})(1 + R^{e}_{i,t+3}) - 1$. Specification (1) includes ISKEW only, (2) includes RA only, (3) includes both RA and ISKEW, (4) includes ISKEW and the control variables, (5) includes RA and the control variables, and (6) includes RA, ISKEW, and the control variables. The

dependent variable is the cumulative excess return over months *t+1* to *t+3*, reported in percentage points. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV logged firm size, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity, COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month, and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken, and Baker, Bloom, and Davis.

Fama-MacBeth Regressions on RA and EPU Regimes

	High EPU Regime						**Low EPU Regime**					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ISKEW	0.349		0.204	-0.487***		-0.527***	0.025		-0.049	-0.155		-0.174
	(0.88)		(0.48)	(-3.07)		(-3.18)	(0.09)		(-0.20)	(-0.82)		(-0.91)
RA		-55.952***	-53.465***		-21.882	-27.997**		-19.783	-18.541		-3.702	-5.552
		(-3.64)	(-3.08)		(-1.62)	(-2.07)		(-1.36)	(-1.40)		(-0.34)	(-0.50)
IVOL				-85.885	-100.249*	-93.853*				3.762	4.487	0.779
				(-1.55)	(-1.86)	(-1.76)				(0.09)	(0.10)	(0.02)
MV				-0.293*	-0.198	-0.266				-0.270	-0.240	-0.269
				(-1.73)	(-1.19)	(-1.59)				(-1.49)	(-1.29)	(-1.47)
BM				-0.060	-0.005	-0.036				0.891***	0.907***	0.887***
				(-0.25)	(-0.02)	(-0.15)				(3.52)	(3.62)	(3.51)
MOM				4.513***	3.659***	4.225***				5.227***	4.835***	5.164***
				(3.65)	(2.92)	(3.33)				(3.76)	(3.51)	(3.72)
BETA				-1.854	-2.196	-2.034				-2.676**	-2.811**	-2.722**
				(-1.37)	(-1.63)	(-1.51)				(-2.31)	(-2.43)	(-2.34)
TURN				-9.313	-9.235	-10.344				-45.357**	-43.004**	-44.311**
				(-0.38)	(-0.38)	(-0.42)				(-2.15)	(-2.00)	(-2.07)
ILLIQ				0.533	0.526	0.538				0.527	0.508	0.526
				(0.89)	(0.87)	(0.89)				(1.10)	(1.07)	(1.11)
COSKEW				-1.139	-1.064	-0.822				0.704	0.502	0.760
				(-0.43)	(-0.39)	(-0.30)				(0.49)	(0.35)	(0.53)
MAX				16.923	15.372	17.838				-0.481	-2.753	0.036
				(1.41)	(1.28)	(1.53)				(-0.05)	(-0.28)	(0.00)
MIN				-17.770	-11.052	-16.179				-26.521**	-24.886*	-25.585*
				(-1.30)	(-0.81)	(-1.19)				(-2.01)	(-1.93)	(-1.92)
REV				6.290***	4.890**	5.731***				6.658***	6.070***	6.515***
				(3.01)	(2.24)	(2.65)				(3.21)	(2.99)	(3.13)
Intercept	5.077***	4.873***	4.710***	10.086***	9.199***	9.835***	2.041	1.914	1.916	7.200***	6.916***	7.164***
	(4.24)	(4.07)	(4.04)	(5.60)	(5.28)	(5.48)	(1.41)	(1.32)	(1.35)	(3.88)	(3.68)	(3.83)

Earlier results from the liquidity, volatility, and arbitrage-cost regime analyses indicate that the RA effect is stronger when arbitrage is more constrained and market conditions are less favorable. A natural progression is to understand the impact of broader macroeconomic uncertainty on RA. This is proxied by the Economic Policy Uncertainty index (Baker, Bloom, & Davis, n.d.).

Table 11 presents the Fama-MacBeth regressions in which the sample is split into periods of high and low Swedish economic policy uncertainty (EPU) with the dependent variable defined as the three-month cumulative excess return. This longer horizon is used because economic policy uncertainty is a broader macroeconomic state variable whose effects may be reflected in stock returns more gradually than firm-level trading frictions. For comparison, the corresponding one-month EPU results for both Swedish and global EPU are reported in appendix C.

Table 11 shows that the RA effect is stronger during high-EPU periods. The coefficient large and negative when entered on its own, remains negative when ISKEW is added, and stays significant in the full specification, although its magnitude declines from -55.952 to -27.997 percentage points. In the low-EPU regime, the coefficient on RA is negative but not statistically significant in any specification. This indicates that the predictive content of RA is present in periods of high Swedish macroeconomic uncertainty.

Looking at ISKEW, the pattern is less clear. In the high-EPU regime, the coefficient becomes negative and statistically significant only once the control variables are added. In the low-EPU regime, it remains insignificant. This suggests that conventional idiosyncratic skewness does not have a stable relation with future returns across Swedish EPU states, especially compared with RA. The Swedish EPU provides similar results as the previous liquidity and volatility analyses. In all three cases, the RA effect is more visible when market conditions are less favorable and uncertainty is higher.

4.4 Which Stocks Drive the RA effect?

This section turns from the question of when the RA effect is strongest to where in the cross-section it is most pronounced. Section 4.3.1 shows that the RA spread varies clearly across market value and book-to-market groups. The negative spread is strongest among stocks with lower market value and lower book-to-market ratios, which points to small growth stocks as the most relevant segment. Therefore, we next set out to test this.

4.4.1 Small-Growth Stocks and RA

Table 12: Size and style sorted portfolios

Table 12: This table reports average next-month returns for residual asymmetry (RA) portfolios formed within 2 by 2 size-style groups. Size is defined using a monthly median split on market value (Small and Big), while style is defined using monthly book-to-market terciles, where the bottom tercile is classified as Growth and the top tercile as Value. Stocks in the middle tercile are excluded. Within each group, stocks are further sorted into RA quintiles. The table reports the average return on the lowest-RA portfolio (Low), the highest-RA portfolio (High) and the High-Low spread (Quintile 5 minus quintile 1) within each size-style cell. Panel A reports equal weighted returns and Panel B reports value weighted returns. Newey-West adjusted t-statistics are reported in parentheses. * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Data sources: FinBas, Riksbanken

Panel A: Equally-weighted quintile RA portfolio returns

Portfolio	Small Growth	Small Value	Big Growth	Big Value
Low	1.466**	1.570***	0.771	2.159***
	(2.28)	(2.76)	(1.48)	(2.92)
High	-0.126	1.515***	0.741*	1.396***
	(-0.24)	(3.09)	(1.78)	(3.75)
High-Low	-1.592***	-0.055	-0.031	-0.763
	(-3.00)	(-0.15)	(-0.10)	(-1.31)

Panel B: Value weighted RA quintile portfolio returns

Portfolio	Small Growth	Small Value	Big Growth	Big Value
Low	1.164*	1.101**	0.701	1.628***
	(1.83)	(1.98)	(1.63)	(2.91)
High	-0.095	1.668***	0.500	1.314***
	(-0.16)	(3.42)	(1.15)	(3.85)
High-Low	-1.258**	0.567	-0.200	-0.314
	(-2.25)	(1.42)	(-0.59)	(-0.73)

In Table 12, stocks are sorted each month into a 2 by 2 size-style framework. Size is split at the monthly median of market value, while style is based on book-to-market terciles, where the lowest tercile is classified as growth and the highest tercile as value. This results in four groups; Small Growth, Small Value, Big Growth, and Big Value. Within each of these groups, stocks are then independently sorted into RA quintiles, and the average next-month excess return is calculated for the lowest-RA and highest-RA portfolios using both equal weighted and value weighted returns.

The results suggest that the negative RA spread is concentrated in small growth stocks. In Panel A, the equal weighted Q5-Q1 spread is -1.592 percentage points and statistically significant in the small growth segment. The corresponding spreads however in small value, big growth and big value are not statistically significant. Panel B shows the same pattern under value weighting. The Q5-Q1 spread remains negative and statistically significant only in small growth, at -1.258 percentage points, while the other three groups again show spreads close to zero and statistically insignificant.

This result indicates that size and style cannot independently account for the RA effect. If size was the relevant dimension, a similar negative spread would be expected in both small growth and small value stocks. If style alone were the relevant dimension, a similar spread would be expected in both small growth and big growth stocks. The negative RA spread appears only where firms are both small and growth oriented.

The earlier state dependent tests show that the RA effect is stronger when liquidity is low and arbitrage costs are high i.e. when corrective trading is more constrained. Table 12 points to a similar conclusion from the cross-section. The effect is specifically concentrated in small growth firms rather than small firms generally.

4.5 Arbitrage Trading and RA

This section concerns economic feasibility of our findings. Statistical significance does not imply that our previous results are implementable, especially in a smaller and less liquid market such as Sweden where turnover and transaction costs may materially erode portfolio profits. This section therefore evaluates the trading performance of RA-based strategies before and after costs. Also, it examines whether the apparent return spreads survive once realistic implementation frictions are considered.

Table 13: Trading the RA Strategy

Table 13: This table reports the gross and net returns of implementable trading strategies formed on residual asymmetry (RA). At the end of each month, stocks are sorted into RA quintiles and held over the subsequent month. The implementable strategy takes a long position in the lowest-RA quintile and a short position in the highest-RA quintile, corresponding to the negative of the conventional RA(5−1) spread. The standard monthly rebalance strategy reconstitutes both legs each month, whereas the buy/hold spread strategy allows positions to remain open as long as stocks stay within adjacent extreme RA buckets. Panel A reports results for the full Swedish stock sample, and Panel B reports results for the small-growth subsample. Gross returns are reported before transaction costs. Net returns are computed by subtracting one-way trading costs based on quoted bid-ask spreads and portfolio turnover, where the monthly stock-level spread is measured as the median daily relative bid-ask spread within the month. Average equal weighted and value weighted trading costs are reported in basis points, and average turnover is measured as the mean of long- and short-leg turnover. Reported return estimates are monthly averages in percent, with Newey-West t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Data sources: FinBas, Riksbanken

Panel A: Full Sample

Strategy	EW gross	EW net	VW gross	VW net	Avg EW cost (bp)	Avg VW cost (bp)	Avg turnover
Standard monthly rebalance	0.595*** (3.02)	0.287 (1.43)	0.322 (1.25)	0.215 (0.83)	30.77	10.64	0.258
Buy/hold spread	0.380** (2.19)	0.219 (1.24)	0.223 (1.00)	0.168 (0.75)	16.16	5.53	0.134

Panel B: Small-Growth Subset

Strategy	EW gross	EW net	VW gross	VW net	Avg EW cost (bp)	Avg VW cost (bp)	Avg turnover

Standard monthly rebalance	0.850** (2.02)	-0.302 (-0.69)	0.503 (1.09)	-0.326 (-0.69)	121.72	88.58	0.651
Buy/hold spread	0.610* (1.70)	-0.046 (-0.13)	0.397 (0.99)	-0.087 (-0.22)	72.11	54.07	0.390

Table 13 presents the performance of two implementable RA-based trading strategies. In both cases, the strategy takes a long position in the lowest-RA portfolio and a short position in the highest-RA portfolio, consistent with the negative relation between RA and future returns documented earlier. The first strategy is a standard monthly rebalancing strategy, in which the long and short portfolios are reconstituted at the end of each month following the new RA sort. The second is a buy-and-hold spread strategy, in which positions are maintained for as long as stocks remain in the extreme RA portfolios. Returns are measured as one-month excess returns. Panel A reports the implementation results for the full sample, while Panel B reports the corresponding results for the small-growth subset. Trading costs are proxied using bid-ask spreads.

Observing Panel A, the gross returns are positive for both trading strategies and strongest for the equal weighted standard monthly rebalance at 0.595% per month with a t-stat of 3.02. The buy-and-hold spread is also positive and significant in equal weighted terms at 0.380%. This means the underlying RA signal does generate a return spread before trading costs in the full sample. However, once trading costs are accounted for, the profitability of the strategies declines. Although the net returns remain positive in the full sample, none of them are statistically significant, which indicates that the predictive power of RA is offset by implementation frictions.

Turning to Panel B for the subset of small-growth stocks, a similar pattern can be seen that gross returns are larger than in the full sample, with the equal weighted standard monthly rebalance generating 0.850% per month and the buy-and-hold spread generating 0.610%, consistent with the earlier finding that the RA effect is strongest in small-growth stocks. However, these stronger gross returns are accompanied by substantially higher turnover and much larger trading costs. As a result, all net returns in the small-growth subset become negative, both under equal weighting and value weighting. This indicates that although the RA signal is economically strongest in the small-growth segment, it is also least implementable there in practice.

5 Discussion

A key result of the paper is that higher RA, or more favorable upside asymmetry in the idiosyncratic return distribution, is associated with lower future stock returns in Sweden, providing support for Hypothesis 1. The Swedish evidence points in the same direction as Chen et al. (2025), but the relation is less uniform across specifications. The effect is strongest in the 12-month equally weighted portfolios, weaker under value weighting, and less pronounced for the 24-month measure, as shown in Section 4.2.1. Value weighted portfolios place greater importance on large-cap stocks and are closer to how capital is allocated in practice. In a small and concentrated market such as Sweden, where a limited number of firms account for a disproportionate share of market value, the weak value weighted results suggest that negative relation between RA and future returns is not widely present amongst larger firms.

Interestingly the descriptive evidence in Sections 4.1.1 and 4.1.2. point towards RA being positively related to firm size and book-to-market i.e. that high-RA stocks are on average larger and more value-oriented than low-RA stocks. A natural assumption is therefore that the negative return relation should be strongest amongst larger firms. However, the size-style sorts in Section 4.4.1 show that the negative RA spread is concentrated in small growth stocks rather than in large or value-oriented firms. The asymmetry effect (negative return relation) therefore appears where firms are both smaller and growth-oriented likely because of small-growth firms specific characteristics, i.e. valuations depend more heavily on uncertain future upside than on current fundamentals leading to higher volatility and lower turnover. Hypothesis 3 therefore receives only partial support as size alone is insufficient to locate the effect. Earlier literature focusing on size alone would have been unlikely to isolate this pattern, and the distinction between where RA is high on average and where it is priced matters for interpreting the Swedish results. Section 4.3 helps explain this concentration, since the earlier heterogeneity and regime tests show that the RA spread becomes more negative in the parts of the market where liquidity is poorer and arbitrage is more constrained.

That cross-sectional concentration also clarifies the mechanism evidence in Section 4.3. The RA effect is strongest when liquidity is poor and arbitrage costs are high, as shown in Sections 4.3.2 and 4.3.4, and these two sets of results provide the most direct support for a friction-based interpretation. Volatility points in the same direction but less clearly, as shown in Section 4.3.3, while the EPU results in Section 4.3.5 are directionally consistent but more distal, since EPU captures broader macroeconomic uncertainty rather than trading frictions directly. This matters for interpretation. A broad risk-based explanation would be more consistent with a relation that appears relatively uniformly across firms and states, whereas a behavioral or mispricing-based explanation predicts that the effect should be strongest where corrective trading is most costly. The Swedish evidence fits the latter pattern better and is therefore more consistent with the limits-to-arbitrage logic in Shleifer and Vishny (1997) and the state-dependent anomaly evidence in Stambaugh, Yu, and Yuan (2012). This provides support for Hypothesis 4.

The paper also shows that the density-based RA measure contains information different from traditional skewness measures which provides support for Hypothesis 2. As shown in Sections 4.1.1 and 4.1.2, high-RA stocks do not resemble conventional lottery stocks on measures such as idiosyncratic skewness, idiosyncratic volatility, and maximum daily return. Instead, it is often the low-RA stocks that appear more lottery-like. The bivariate sorts and Fama-MacBeth regressions in Sections 4.2.2 and 4.2.3 reinforce this interpretation. The negative relation associated with RA survives conditioning on a comprehensive set of firm characteristics, and conventional idiosyncratic skewness adds little once RA is included. The Swedish results are consistent with the argument in Chen et al. (2025) that density-based asymmetry captures distributional information not reflected in third moment statistics.

Relative to the European literature, the Swedish results help clarify the pattern of prior literature being mixed. Annaert, De Ceuster, and Verstegen (2013) and Walkshäusl (2014) document negative pricing of lottery-like payoffs in European equities using MAX-based measures, while Annaert, De Ceuster, and Van Cappellen (2023) find that average skewness does not significantly predict returns in the euro area. These findings indicate that the asymmetry-return relation in Europe is sensitive to how asymmetry is measured. The Swedish results support this as the RA effect is present and significant, while conventional idiosyncratic skewness yields weaker and less reliable results in the same sample. Mixed European evidence on skewness-based predictability may therefore partly reflect a measurement limitation rather than the absence of asymmetry pricing. Importantly however, the Swedish results are more conditional than the U.S. evidence presented by Chen et al. (2025), which suggests that market structure plays an independent role. In a smaller and more concentrated setting, asymmetry pricing appears clearer in specific segments rather than broadly across the cross-section.

The persistence results in Section 4.1.3 add a qualification to the measurement discussion. The RA measure is clearly persistent, indicating that it captures more than transitory estimation noise. At the same time, the comparison between the 12-month and 24-month measures shows that greater persistence does not necessarily improve predictive usefulness: the longer-window measure is more stable but less informative for next-month return prediction.

6 Conclusion

This paper examines whether and how idiosyncratic return asymmetry is priced in the Swedish equity market. Using the density-based RA measure developed by Chen and Liu (2024), we test whether higher asymmetry predicts lower future returns, whether RA contains information beyond traditional skewness- and lottery-based proxies, and whether the effect is stronger where arbitrage is more difficult. The results support a negative relation between RA and subsequent stock returns but show that the effect is conditional rather than broad. It is concentrated in small growth stocks and other high-friction segments, and the predictive content of RA is not fully absorbed by conventional skewness measures or other lottery-related characteristics.

These findings suggest that asymmetry can be priced in a smaller European market, but the effect varies across the cross-section. Relative to the U.S. evidence, the Swedish effect is more conditional and more closely tied to liquidity and arbitrage frictions. Relative to the mixed European literature, the results suggest that part of the difficulty in detecting asymmetry pricing likely lies in how asymmetry is measured. The density-based framework reveals a pricing relation that is less visible with traditional skewness-based proxies, while also showing that the effect is concentrated where firms are hardest to value and hardest to arbitrage.

Several questions remain open. Although the results are more consistent with a limits-to-arbitrage interpretation than with a broad risk-premium explanation, the analysis does not identify the investor channel directly. It therefore remains unclear whether the Swedish asymmetry effect reflects retail demand for lottery-like payoffs, institutional constraints on corrective trading, or broader differences in investor clientele. The paper also does not fully resolve which estimation horizon is most appropriate for measuring firm-level asymmetry: the 24-month RA measure is more persistent than the 12-month measure but less informative for return prediction, and the right trade-off between stability and timeliness remains an open question.

These limitations point to several directions for future research. Linking RA to stock-level ownership data such as institutional ownership, household participation, or trading by investor type could help distinguish the mechanisms underlying the Swedish asymmetry effect and connect it more directly to the investor channels the current analysis cannot separate. Extending the analysis to other Nordic markets such as Denmark, Norway, and Finland would help determine whether the Swedish pattern is country-specific or reflects a broader feature of smaller developed equity markets. A further step would be to compare the density-based RA measure more directly with alternative asymmetry measures, including option-implied skewness where data availability permits.

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8 Appendix

8.1 Appendix A: Data Quality

In Appendix A we address some key issues with the data quality of our main data source FinBas. Appendix A1 addresses key issues with N/A values in the dataset, Appendix A2 and A3 addresses key issues regarding the RA estimation eligibility. The starting year for the sample period is ultimately a decision between data quality and preserving sample length.

8.1.1 Appendix A1: N/A values

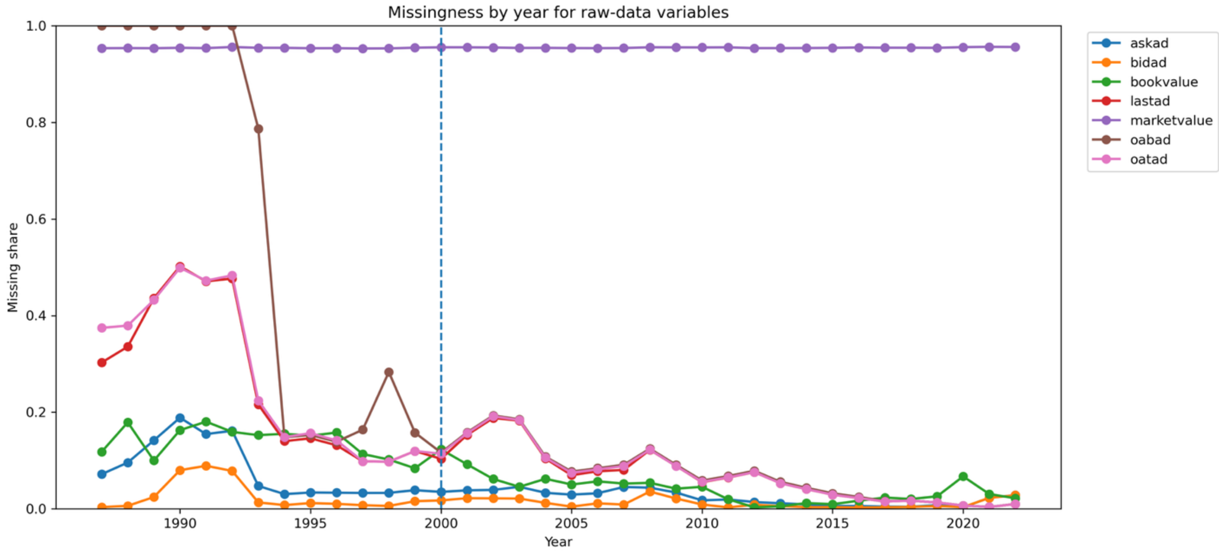

Figure A1: N/A Values in FinBas Stockholm Stock Exchange Data

Note: This figure reports the yearly share of missing observations for selected variables in the raw FinBas Stockholm Stock Exchange dataset. Missingness is calculated separately for quoted ask prices (askad), bid prices (bidad), book value (bookvalue), closing prices (lastad), market value (marketvalue), traded value (oabad), and traded volume in shares (oatad). The vertical dashed line marks the year 2000, which is used as the starting point of the final sample period. The figure shows that data availability improves substantially after the early 1990s, although the timing and degree of improvement differ across variables. In particular, price and trading-volume variables become considerably more complete over time, while some raw variables, such as marketvalue, remain highly incomplete throughout. The figure is therefore intended as a raw-data diagnostic rather than as evidence on the final usability of the analysis sample.

Figure A1 above provides missingness share in key columns of our main data panel from FinBas, which indicates clear incompleteness in the dataset before 1995.

8.1.2 Appendix A2: RA Estimation Eligibility

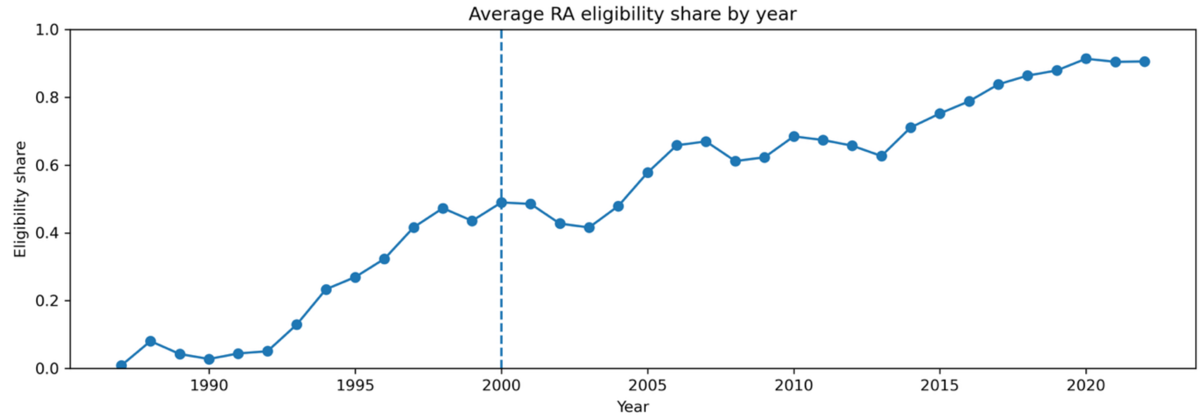

Figure A2: RA Eligibility Share per year
Note: This figure reports the yearly share of stock-months that satisfy the minimum data requirements for RA estimation. A stock-month is classified as eligible if the stock has at least 200 nonzero daily return observations in the preceding 250 trading days and a non-missing positive month-end price. The dashed vertical line marks the year 2000, which is used as the starting point of the final sample period.

Figure A2 examines the share of the observations that pass the later screens included during the estimation of RA. The eligibility markedly increases post 1990 and passes roughly 50% around late 1990s and around year 2000.

8.1.3 Appendix A3: RA Estimation Sensitivity

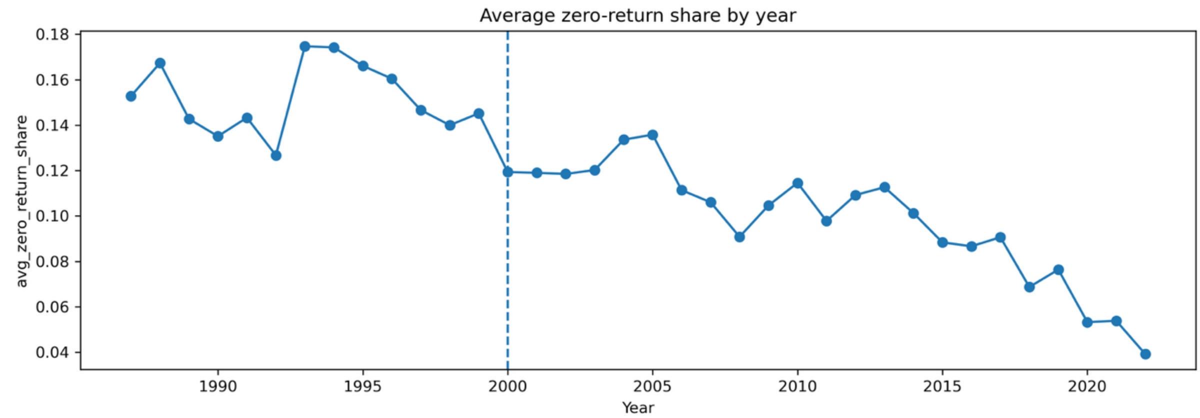

Figure A3: Average Zero-return Share by Year
Note: This figure reports the average yearly share of daily zero returns in the raw FinBas Stockholm Stock Exchange data. The zero-return share is calculated at the stock-month level and then averaged within each year.

Figure A3 shows that the average share of zero daily returns is materially higher before 2000 than in the later sample, which is consistent with thinner trading activity and a greater prevalence of stale prices in the earlier years. This is particularly relevant for the present study, since the estimation of RA relies on a sufficiently rich history of nonzero daily returns.

8.2 Appendix B: Kernel Settings for RA Estimation

Table B: Kernel Settings for RA Estimations

Table B: This table presents the kernel settings used during the estimation of the RA.

Setting	Value	Explanation
Bandwidth Selection Grid Size	31	The bandwidth is selected by testing 31 candidate bandwidths. This is a numerical implementation of likelihood cross-validation to preserve computational speed and proper validation.
Mode Estimation Grid Size	1001	The estimated density is evaluated on 1001 grid points to find the mode of the residual distribution.
Density Grid Padding	1001	The RA integral is approximated using 1001 grid points around the estimated mode.
Numerical Integration Grid Size	6	The density grid is extended beyond the observed residual range by six bandwidths to avoid cutting off the tails of the Gaussian Kernel

8.3 Appendix C: Global EPU and Swedish EPU for One-Month Holding Period

Table C1: Swedish EPU and RA 1-month Holding Period

Table C1: This table reports monthly Fama-MacBeth cross-sectional regressions of next-month excess stock returns estimated separately in high- and low-Swedish-EPU regimes, where the regimes are defined by splitting the sample at the mean value of the Swedish Economic Policy Uncertainty (EPU) index. The estimated monthly cross-sectional regression is $R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}$ where $X_{i,t}$ is the vector of control variables. Specification (1) includes ISKEW only, (2) includes RA only, (3) includes both RA and ISKEW, (4) includes ISKEW and the control variables, (5) includes RA and the control variables, and (6) includes RA, ISKEW, and the control variables. The dependent variable is next-month excess return, reported in percentage points. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV logged firm size, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity, COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month, and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken, and Baker, Bloom, and Davis.

Fama-MacBeth Regressions on RA and EPU Regimes

	High EPU Regime						Low EPU Regime					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ISKEW	-0.004		-0.023	-0.093		-0.102	0.188		0.151	0.069		0.053
	(-0.03)		(-0.20)	(-1.17)		(-1.27)	(1.11)		(0.92)	(0.67)		(0.51)
RA		-9.023	-9.756*		-7.368	-8.460		-14.517**	-10.156*		-7.208	-6.798
		(-1.62)	(-1.69)		(-1.05)	(-1.23)		(-2.25)	(-1.95)		(-1.50)	(-1.43)
IVOL				-43.300	-46.623	-44.429				-45.717**	-44.511**	-46.232**
				(-1.44)	(-1.56)	(-1.49)				(-2.09)	(-1.98)	(-2.12)
MV				-0.046	-0.028	-0.042				-0.150*	-0.146*	-0.143*
				(-0.59)	(-0.37)	(-0.55)				(-1.92)	(-1.84)	(-1.84)
BM				0.067	0.084	0.076				0.250**	0.256***	0.257***
				(0.61)	(0.78)	(0.70)				(2.52)	(2.62)	(2.62)
MOM				1.276**	1.083**	1.172**				1.538**	1.431**	1.484**
				(2.40)	(2.09)	(2.13)				(2.25)	(2.17)	(2.17)
BETA				-0.740	-0.822	-0.805				-0.965*	-1.032**	-0.995*
				(-1.14)	(-1.26)	(-1.23)				(-1.84)	(-1.97)	(-1.89)
TURN				-13.905	-14.097	-14.732				-13.883*	-13.493	-14.219*
				(-1.52)	(-1.61)	(-1.61)				(-1.73)	(-1.63)	(-1.76)
ILLIQ				0.135	0.130	0.129				0.160	0.146	0.158
				(0.81)	(0.81)	(0.79)				(1.00)	(0.91)	(1.00)
COSKEW				0.914	1.011	1.020				-0.592	-0.544	-0.514
				(0.74)	(0.81)	(0.81)				(-0.82)	(-0.72)	(-0.69)
MAX				6.136	6.119	6.414				5.155	4.461	5.111
				(0.94)	(0.90)	(0.98)				(0.99)	(0.84)	(0.98)
MIN				-0.703	0.560	-0.502				4.701	5.208	4.955
				(-0.08)	(0.07)	(-0.06)				(0.78)	(0.86)	(0.82)
REV				1.710	1.204	1.509				2.398**	2.236**	2.317**
				(1.27)	(0.84)	(1.08)				(2.52)	(2.38)	(2.41)
Intercept	1.102**	1.049*	1.024*	2.535***	2.343***	2.463***	1.028*	1.004*	0.952*	3.299***	3.264***	3.216***
	(2.03)	(1.89)	(1.88)	(3.25)	(3.04)	(3.17)	(1.92)	(1.87)	(1.81)	(4.45)	(4.43)	(4.37)

Table C2: Global EPU and RA 1-month Holding Period

Table C2: Global EPU and RA over One-Month Holding Periods. This table reports monthly Fama-MacBeth cross-sectional regressions of next-month excess stock returns estimated separately in high- and low-global-EPU regimes, where the regimes are defined by splitting the sample at the mean value of the Global Economic Policy Uncertainty (EPU) index. The estimated monthly cross-sectional regression is $R_{i,t+1} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}$ where $X_{i,t}$ is the vector of control variables. Specification (1) includes ISKEW only, (2) includes RA only, (3) includes both RA and ISKEW, (4) includes ISKEW and the control variables, (5) includes RA and the control variables, and (6) includes RA, ISKEW, and the control variables. The dependent variable is next-month excess return, reported in percentage points. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV logged firm size, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity, COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month, and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken, and Baker, Bloom, and Davis.

Panel A: Fama-MacBeth Regressions on RA and EPU Regimes

	High EPU Regime						Low EPU Regime					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ISKEW	0.225		0.219	-0.134*		-0.129*	0.044		0.004	0.064		0.043
	(0.92)		(0.88)	(-1.72)		(-1.65)	(0.47)		(0.04)	(0.77)		(0.52)
RA		-11.553	-6.532		0.510	-1.605		-12.402**	-11.687**		-11.149**	-10.460**
		(-1.54)	(-1.07)		(0.08)	(-0.26)		(-2.21)	(-2.27)		(-2.17)	(-2.05)
IVOL				-76.121**	-77.932**	-76.358**				-29.031	-29.267	-30.083
				(-2.20)	(-2.32)	(-2.23)				(-1.39)	(-1.38)	(-1.43)
MV				-0.138	-0.108	-0.140				-0.088	-0.088	-0.079
				(-1.51)	(-1.18)	(-1.57)				(-1.15)	(-1.13)	(-1.04)
BM				-0.043	-0.019	-0.038				0.277***	0.281***	0.286***
				(-0.43)	(-0.19)	(-0.39)				(2.92)	(3.03)	(3.05)
MOM				1.562***	1.355***	1.546***				1.356**	1.243**	1.251**
				(3.02)	(2.81)	(3.02)				(2.24)	(2.10)	(2.06)
BETA				-0.021	-0.053	0.008				-1.288**	-1.383***	-1.370***
				(-0.03)	(-0.08)	(0.01)				(-2.50)	(-2.67)	(-2.65)
TURN				-13.000*	-12.540*	-13.849*				-14.336*	-14.359*	-14.736*
				(-1.67)	(-1.81)	(-1.84)				(-1.74)	(-1.74)	(-1.77)
ILLIQ				0.556*	0.548*	0.546*				-0.053	-0.065	-0.054
				(1.87)	(1.89)	(1.88)				(-1.29)	(-1.52)	(-1.34)
COSKEW				-1.233	-1.292	-1.215				0.705	0.839	0.831
				(-1.13)	(-1.17)	(-1.11)				(0.89)	(1.03)	(1.01)
MAX				13.749*	13.457*	14.003*				1.520	1.066	1.537
				(1.79)	(1.73)	(1.83)				(0.32)	(0.22)	(0.32)
MIN				4.162	5.486	3.895				1.458	2.050	1.937
				(0.45)	(0.63)	(0.43)				(0.23)	(0.33)	(0.31)
REV				3.489**	3.181**	3.427**				1.408	1.096	1.240
				(2.42)	(2.25)	(2.36)				(1.51)	(1.13)	(1.31)
Intercept	1.475**	1.526***	1.417**	3.093***	2.809***	3.068***	0.856*	0.775	0.769	2.906***	2.892***	2.800***
	(2.53)	(2.65)	(2.47)	(3.39)	(3.13)	(3.45)	(1.72)	(1.56)	(1.57)	(4.17)	(4.12)	(4.04)

8.4 Appendix D: Three-Month Holding Period Robustness Test

Appendix D presents additional robustness tests using a three-month holding period instead of the baseline specification of next-month ahead excess returns. Thus, in this section, the dependent variable is the three-month cumulative excess returns.

8.4.1 Univariate Portfolio Sort and Fama-MacBeth Regressions: Three-Month Holding Period

Below, Table D1 presents the univariate portfolio sort results using three-month cumulative excess returns as the return measure. Overall, the results show a pattern consistent with the main one-month results reported in Table 5. Portfolios with higher RA continue to earn lower subsequent returns than portfolios with lower RA. This suggests that the negative relation between RA and future stock returns extends beyond the immediate next month and persists over a longer three-month horizon.

Table D2 presents the Fama-MacBeth regressions of RA and a set of control variables on the three-month cumulative excess returns

Table D1: Univariate Portfolio Sort of RA

Table D1: This table reports next-month excess returns in percentage points for portfolios sorted on RA. At the end of each month, stocks are sorted into portfolios based on RA estimated from daily residuals over either a 12-month or 24-month estimation window. Panel A reports results for RA-sorted quintile portfolios, while Panel B reports results for RA-sorted decile portfolios. For each specification, the table presents equal weighted and value weighted average excess returns as well as CAPM alphas, Fama-French three-factor alphas and Carhart four-factor alphas. **Low** denotes the portfolio with the lowest RA, and High denotes the portfolio with the highest RA. The High-Low row reports the return spread between the highest-RA and lowest-RA portfolios. The return is defined as the 3-month cumulative excess return return $R^{e,(3)}_{i,t+1:t+3} = (1 + R^e_{i,t+1})(1 + R^e_{i,t+2})(1 + R^e_{i,t+3}) - 1.$, Newey-West t-statistics are reported in parentheses. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31. Data sources: FinBas, Riksbanken

Panel A: Quintile Portfolio Sorts

	12-month estimation period								24-month estimation period							
	Equal weighted				Value weighted				Equal weighted				Value weighted			
	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha
Low	4.521***	2.070***	1.777***	1.918*** (3.59)	3.076***	0.948*	0.826	0.857	4.230***	1.805***	1.462***	1.561**	3.731***	1.824***	1.582***	0.675
	(3.63)	(3.80)	(3.95)		(2.90)	(1.73)	(1.18)	(1.13)	(3.28)	(2.84)	(2.72)	(2.53)	(3.92)	(3.83)	(3.36)	(1.31)
2	3.641***	1.187**	0.795**	0.644	2.675***	0.519	0.397	0.368	3.491***	1.036**	0.666*	0.308	2.951***	0.949**	0.527	0.355
	(2.96)	(2.31)	(2.04)	(1.60)	(2.59)	(1.39)	(1.06)	(0.78)	(2.86)	(2.11)	(1.75)	(0.73)	(3.08)	(2.07)	(1.15)	(0.66)
3	3.049***	0.675*	0.071	-0.168	2.132**	-0.003	-0.503	-0.719	3.140***	0.754*	0.075	0.026	2.062*	-0.194	-0.228	0.343
	(2.65)	(1.66)	(0.22)	(-0.52)	(2.11)	(-0.01)	(-1.21)	(-1.54)	(2.70)	(1.66)	(0.20)	(0.07)	(1.91)	(-0.51)	(-0.58)	(0.76)
4	3.612***	1.387***	0.695**	0.480	1.959**	-0.222	-0.487	-0.339	3.524***	1.292***	0.652**	0.561**	2.318**	0.191	0.113	0.487
	(3.43)	(3.44)	(1.98)	(1.55)	(1.98)	(-0.62)	(-1.36)	(-0.76)	(3.31)	(3.48)	(2.24)	(2.01)	(2.37)	(0.59)	(0.32)	(1.21)
High	2.929***	0.728*	-0.115	0.030	2.264***	0.385	0.475	0.315	3.371***	1.163***	0.370	0.448	2.444***	0.497*	0.446	0.204
	(2.72)	(1.74)	(-0.32)	(0.08)	(2.68)	(1.28)	(1.47)	(0.89)	(3.22)	(3.26)	(1.27)	(1.46)	(2.76)	(1.91)	(1.60)	(0.66)
High-Low	**-1.592***	**-1.342***	**-1.893***	**-1.888*** (-**	**-0.811**	**-0.564**	**-0.352**	**-0.542**	**-0.859**	**-0.641**	**-1.092***	**-1.113***	**-1.287***	**-1.327***	**-1.136***	**-0.471**
	(-3.36)	**(-2.96)**	**(-4.45)**	**4.06)**	**(-1.27)**	**(-0.78)**	**(-0.39)**	**(-0.57)**	**(-1.38)**	**(-1.07)**	**(-1.89)**	**(-1.92)**	**(-2.33)**	**(-2.37)**	**(-1.87)**	**(-0.70)**

Panel B: Decile Portfolio Sorts

	12-month estimation period								24-month estimation period							
	Equal weighted				Value weighted				Equal weighted				Value weighted			
	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha	Average return	CAPM alpha	FF3 alpha	Carhart4 alpha
Low	4.593***	2.223***	1.988***	1.986***	3.268***	1.127*	0.931	0.809	4.549***	2.042**	1.767***	2.222**	4.176***	2.152***	1.928***	1.167
	(3.66)	(3.53)	(3.50)	(2.99)	(2.90)	(1.71)	(1.12)	(0.93)	(3.17)	(2.52)	(2.61)	(2.27)	(3.94)	(3.87)	(3.66)	(1.53)
2	4.452***	1.919***	1.568***	1.851***	3.587***	1.467**	1.413**	1.404*	3.918***	1.574**	1.164*	0.896	3.679***	1.708***	1.129*	0.609
	(3.38)	(3.10)	(2.88)	(3.06)	(3.26)	(2.56)	(2.19)	(1.83)	(3.01)	(2.26)	(1.66)	(1.51)	(3.56)	(2.85)	(1.92)	(0.87)
3	3.678***	1.344**	0.993*	0.804 (1.46)	2.667**	0.468	0.101	-0.223	3.406***	1.009*	0.508	0.092	2.280**	0.227	-0.263	-0.746
	(3.04)	(2.17)	(1.90)		(2.55)	(1.07)	(0.23)	(-0.43)	(2.68)	(1.69)	(1.11)	(0.17)	(2.30)	(0.42)	(-0.51)	(-1.24)
4	3.602***	1.028**	0.596	0.486 (1.18)	2.708**	0.486	0.377	0.044	3.572***	1.057*	0.819	0.530	3.532***	1.419***	1.098*	0.954
	(2.77)	(2.06)	(1.51)		(2.40)	(1.03)	(0.86)	(0.08)	(2.85)	(1.92)	(1.60)	(0.95)	(3.33)	(2.66)	(1.94)	(1.46)
c5	2.776**	0.478	-0.168	-0.243	2.935***	0.792	0.048	-0.193	3.425***	1.084**	0.327	0.402	2.134**	-0.029	-0.527	-0.333
	(2.46)	(1.10)	(-0.47)	(-0.63)	(2.84)	(1.56)	(0.10)	(-0.34)	(2.92)	(2.07)	(0.70)	(0.87)	(2.02)	(-0.07)	(-1.08)	(-0.57)
6	3.322***	0.871*	0.311	-0.096	1.674	-0.444	-0.905*	-1.157**	2.851**	0.420	-0.179	-0.355	2.150*	-0.156	-0.296	0.154
	(2.74)	(1.85)	(0.71)	(-0.25)	(1.58)	(-0.89)	(-1.70)	(-1.96)	(2.38)	(0.88)	(-0.46)	(-0.82)	(1.86)	(-0.29)	(-0.58)	(0.26)
7	3.385***	1.110**	0.426	0.450 (1.16)	2.594**	0.450	-0.127	0.175	3.542***	1.217***	0.730**	0.793**	2.679**	0.515	0.471	0.692
	(3.12)	(2.54)	(1.08)		(2.51)	(0.86)	(-0.22)	(0.24)	(3.15)	(3.02)	(2.19)	(2.44)	(2.52)	(1.27)	(1.11)	(1.46)
8	3.837***	1.661***	0.960*	0.513 (1.31)	1.707*	-0.531	-0.700**	-0.598	3.508***	1.369***	0.578	0.334	2.260**	0.147	-0.168	0.087
	(3.53)	(3.21)	(1.84)		(1.66)	(-1.39)	(-1.98)	(-1.39)	(3.36)	(3.05)	(1.53)	(0.97)	(2.26)	(0.34)	(-0.38)	(0.18)
9	3.012***	0.775*	0.004	0.198 (0.48)	2.162**	0.301	0.394	0.109	3.223***	1.094***	0.419	0.476	1.612	-0.520	-0.415	-0.479
	(2.73)	(1.91)	(0.01)		(2.51)	(0.70)	(1.02)	(0.29)	(3.17)	(2.87)	(1.13)	(1.17)	(1.63)	(-1.52)	(-1.23)	(-1.20)
High	2.853***	0.687	-0.228	-0.135	2.326**	0.279	0.495	0.664	3.523***	1.237***	0.329	0.427	3.413***	1.525***	1.295***	1.067***
	(2.64)	(1.39)	(-0.54)	(-0.28)	(2.41)	(0.72)	(1.36)	(1.39)	(3.16)	(2.84)	(0.92)	(1.08)	(3.85)	(3.64)	(3.56)	(2.63)

High-Low	**- 1.740*** (-2.74)**	**-1.536** (-2.47)**	**- 2.216*** (-3.48)**	**-2.122*** (- 3.15)**	**-0.942 (-1.39)**	**-0.848 (-1.15)**	**-0.436 (-0.46)**	**-0.146 (-0.14)**	**-1.026 (-1.16)**	**-0.805 (-1.03)**	**-1.438** (-2.03)**	**-1.795* (-1.83)**	**-0.763 (-1.09)**	**-0.627 (-0.92)**	**-0.633 (-0.95)**	**-0.100 (-0.12)**

Table D2: Fama-MacBeth regressions with three-month holding period

Table D2: This table reports the monthly Fama-MacBeth cross-sectional regressions of next month excess stock returns on RA and a set of firm characteristics. The estimated monthly cross-sectional regression is $R^{(3)}_{i,t+1:t+3} = \alpha_t + \beta_{RA,t} RA_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1:t+3}$. Where $X_{i,t}$ is a vector of controlled variables defined below and the dependent variable is defined as the 3-month cumulative excess return $R^{e,(3)}_{i,t+1:t+3} = (1 + R^e_{i,t+1})(1 + R^e_{i,t+2})(1 + R^e_{i,t+3}) - 1$. R1-R12 present alternative model specifications with an increasingly rich set of control variables. The dependent variable is next-month excess return and the results are in percentage point units. RA denotes residual asymmetry, ISKEW idiosyncratic skewness, IVOL idiosyncratic volatility, MV firm size logged, BM book-to-market, MOM momentum, BETA market beta, TURN share turnover, ILLIQ Amihud illiquidity (for readability ILLIQ is scaled by 10^6), COSKEW coskewness, MAX the maximum daily return within the month, MIN the minimum daily return within the month and REV short-term reversal. Reported coefficients are the time series averages of the monthly cross-sectional slope estimates, with Newey-West t-statistics in parentheses. *, * and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is 2000-01-03 to 2022-12-31.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
ISKEW		0.061	0.282	-0.095	-0.055	-0.317**	-0.234*	-0.222	-0.214	-0.223	-0.275**	-0.327**
		(0.23)	(1.14)	(-0.64)	(-0.38)	(-2.34)	(-1.68)	(-1.61)	(-1.53)	(-1.61)	(-1.98)	(-2.32)
RA	-35.539***	-33.754***	-38.236***	-32.799***	-33.501***	-19.245*	-23.458**	-22.525**	-20.862**	-21.036**	-18.345*	-15.281
	(-2.86)	(-2.69)	(-3.29)	(-3.07)	(-3.32)	(-1.88)	(-2.47)	(-2.36)	(-2.15)	(-2.13)	(-1.85)	(-1.51)
IVOL			-60.641***	-92.022***	-83.947***	-70.285***	-54.389***	-56.160***	-58.327***	-58.155***	-111.977***	-40.240
			(-3.02)	(-4.81)	(-4.80)	(-4.32)	(-3.43)	(-3.54)	(-3.66)	(-3.64)	(-4.41)	(-1.10)
MV				-0.425***	-0.352***	-0.455***	-0.187	-0.215	-0.209	-0.213	-0.241	-0.268*
				(-4.24)	(-3.20)	(-4.12)	(-1.25)	(-1.43)	(-1.38)	(-1.44)	(-1.64)	(-1.89)
BM					0.334*	0.339*	0.317*	0.453**	0.474**	0.487**	0.482**	0.487**
					(1.72)	(1.82)	(1.80)	(2.28)	(2.33)	(2.41)	(2.41)	(2.48)
MOM						4.992***	4.495***	4.621***	4.566***	4.600***	4.673***	4.757***
						(4.28)	(4.31)	(4.42)	(4.30)	(4.33)	(4.38)	(4.31)
BETA							-2.868***	-2.725***	-2.603***	-2.500**	-2.603***	-2.424**
							(-3.01)	(-2.84)	(-2.72)	(-2.54)	(-2.60)	(-2.52)
TURN								-23.791	-26.966	-27.309	-28.029	-29.588*
								(-1.26)	(-1.39)	(-1.39)	(-1.48)	(-1.65)
ILLIQ									0.545	0.546	0.562	0.531
									(1.28)	(1.28)	(1.31)	(1.27)
COSKEW										0.003	-0.117	0.074
										(0.00)	(-0.08)	(0.05)
MAX											20.886***	7.753
											(3.03)	(0.94)
MIN												-21.508**
												(-2.14)
REV												6.175***
												(3.99)
Intercept	3.203***	3.133***	4.402***	8.597***	7.981***	8.065***	7.667***	7.920***	7.834***	7.836***	8.221***	8.322***
	(2.94)	(2.94)	(4.36)	(6.10)	(5.54)	(5.64)	(5.26)	(5.38)	(5.25)	(5.28)	(5.54)	(5.75)

8.5 Artificial Intelligence

ChatGPT was used as a supporting tool during the preparation of this thesis. Its use was limited to assistance with LaTeX and table formatting, equation presentation, code structuring, and language editing. On the advice of our tutor, it was used mainly to improve the quality of our writing to match financial journals. This included improving clarity, shortening paragraphs, and suggesting better wording and sentence/paragraph structure. It also assisted with code organization/readability and the identification of potential coding issues. ChatGPT was not used to carry out any empirical analysis, produce results, or formulate the paper's conclusions. All analysis, interpretation, and conclusions were developed independently by the authors.

The use of ChatGPT also involved risks. Suggested text could introduce stylistic bias or interpretations that were not fully supported by the results, and suggested code could contain errors or make unsuitable assumptions. To manage these risks, all suggestions were reviewed manually before being used. Writing suggestions were checked to ensure that they reflected our intended meaning and remained consistent with the thesis' argument, results, and cited literature. Code-related suggestions were treated as tentative and were always double-checked through our own review and testing. ChatGPT was therefore used only as a support tool, while all substantive judgments and final decisions remained our own.