Research-Thesis: To what extent does salience theory explain the cross-section of stock returns in the german equity market, and how do different market states influence this relationship?

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TO WHAT EXTENT DOES SALIENCE THEORY EXPLAIN THE CROSS-SECTION OF STOCK RETURNS IN THE GERMAN EQUITY MARKET, AND HOW DO DIFFERENT MARKET STATES INFLUENCE THIS RELATIONSHIP?

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List of Abbreviations

BM	Book-to-Market Ratio
CDAX	Composite DAX Index
CMA	Conservative Minus Aggressive
dscd	Firm Identifier
EW	Equally-Weighted
FF6	Fama-French six-factor model
GPS	Global Preference Survey
HML	High Minus Low
LS	Long-Short
LS_ew	Long-Short Equally-Weighted
LS_vw	Long-Short Value-Weighted
MKT	Market Factor
MOM	Momentum
REV	Short-Term Reversal
RMW	Robust Minus Weak
ROA	Return on Assets
SMB	Small Minus Big
VDAX	Volatility Index DAX
VW	Value-Weighted

1. Introduction

A central assumption of traditional asset pricing theory is that investors process all available information rationally and symmetrically (Fama, 1970). Yet a large and growing body of evidence in behavioral finance challenges this view, documenting systematic patterns in how individuals allocate attention and form expectations under risk. Salience theory offers a unified framework for understanding these patterns, proposing that decision-makers disproportionately focus on outcomes that are most distinctive relative to their context and consequently overweight such outcomes in their probability assessments (Bordalo et al., 2012, 2013). Applied to financial markets, this mechanism implies that stocks whose most prominent past return realizations are positive tend to attract excess demand, become temporarily overpriced, and subsequently earn lower returns, while stocks with salient negative realizations tend to be underpriced and earn higher subsequent returns. This generates a testable prediction for the cross-section of expected stock returns that is distinct from conventional risk-based explanations (Bordalo et al., 2013; Cosemans & Frehen, 2021).

The empirical asset pricing implications of salience theory have received growing attention in recent years. Evidence from the US market documents a robust negative relation between a stock's salience measure and its future returns, consistent with the temporary overpricing of salient stocks (Cosemans & Frehen, 2021). International evidence across 48 countries broadly confirms this negative relation, while also revealing important limitations: the effect is concentrated among microcap firms and is primarily realized following periods of elevated market volatility and severe downturns, rather than being broadly pervasive across firm sizes and market conditions (Cakici & Zaremba, 2022). Together, these studies establish salience as an empirically relevant but contextually dependent driver of cross-sectional return differences.

Despite this progress, the existing literature leaves important questions unanswered. Prior international evidence treats Germany as one observation among many in a broad cross-country sample, without examining the specific conditions under which salience-driven mispricing arises and persists in this market. This omission is notable for two reasons. First, Germany is among the largest equity markets in Europe, with a long history of listed firms spanning diverse industries and size segments, making it a substantively important setting for testing behavioral asset pricing theories. Second, Germany's equity market exhibits structural and behavioral characteristics that differ from the US context in which salience theory was originally developed, making it a distinct and informative out-of-sample testing ground. Survey-based evidence suggests that German individuals display higher uncertainty avoidance and lower average risk tolerance than their US counterparts (Falk et al., 2018; *The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.), which may translate into a stronger tendency to overweight salient return outcomes.

This thesis examines the extent to which salience theory can explain the cross-section of stock returns in the German equity market and investigates how different market states influence this relationship. The analysis is based on German equity data spanning December 1988 to December 2023 and employs quintile portfolio sorts, Fama-MacBeth cross-sectional regressions, and a market state analysis using the VDAX implied volatility index and the SAFE Manager Sentiment Index. A country-specific recalibration of the salience distortion parameter, motivated by the behavioral evidence outlined above, is additionally examined.

The results provide evidence consistent with salience-driven mispricing in the German equity market. Stocks with higher salience measures earn lower risk-adjusted returns, an effect that is primarily concentrated among smaller firms and remains relatively stable across market states, suggesting that it reflects a persistent behavioral mechanism rather than a conditionally amplified anomaly.

This thesis makes three contributions to the literature. First, it provides focused empirical evidence on salience-based asset pricing in the German equity market, complementing the country-level observations embedded in international studies with a dedicated long-sample analysis. Second, it extends the market state analysis to a German context using country-appropriate proxies for uncertainty and sentiment. Third, it introduces a behaviorally motivated country-specific calibration of the salience distortion parameter, illustrating both the scope and the limits of adapting behavioral models to different investor populations. The remainder of this thesis is structured as follows. Section 2 develops the theoretical framework and section 3 describes the data and empirical methods. Section 4 presents the results, section 5 discusses the findings and outlines implications and limitations, and section 6 concludes.

2. Theoretical Framework

Understanding why salience theory may explain the cross-section of stock returns requires building a layered theoretical foundation. This section develops that foundation in five steps. It begins with the core mechanics of salience theory as a model of decision-making under risk, establishing the formal properties of the salience function and the distortion parameter that governs the strength of attentional biases. It then extends these individual-level mechanisms to the market equilibrium setting of asset pricing, showing how salience distortions translate into predictable patterns of overvaluation and undervaluation across stocks. The following section introduces limits to arbitrage as the complementary mechanism that allows such mispricings to persist rather than being immediately corrected by rational investors. The next section examines how salience effects vary over time with aggregate market conditions, drawing on both US and international evidence. Finally, the last section situates the analysis in the specific institutional and behavioral context of the German equity market, identifying the structural features and investor characteristics that shape how salience-driven mispricing is likely to manifest in this setting.

2.1. Salience Theory and Decision-Making under Risk

While the efficient market hypothesis assumes that investors process all available information rationally and symmetrically, a growing body of research in behavioral finance demonstrates that human attention is inherently selective. Salience theory formalizes this insight by proposing that decision-makers disproportionately focus on outcomes that are most distinctive relative to their context. Rather than evaluating all payoffs equally, investors overweight those that stand out, leading to systematic distortions in decision-making under risk (Bordalo et al., 2012).

The central departure of salience theory from classical expected utility theory concerns the independence axiom, which requires that a rational decision-maker's preference ordering between two lotteries should not change when an identical consequence is added to both. The well-known Allais paradox violates this axiom, and salience theory provides an intuitive explanation grounded in attention. The Allais paradox describes the empirical finding that individuals systematically violate the independence axiom when a common consequence is added to two lotteries (Allais, 1953). When a common consequence is added to two lotteries, it changes the comparative context in which each payoff is evaluated. As a result, the salience ranking of outcomes shifts, redirecting investor attention toward different dimensions of the choice. In one configuration, the downside payoff differs most starkly across lotteries and thus becomes salient, causing investors to overweight potential losses and exhibit risk aversion. In another configuration, it is the upside that stands out, generating risk-seeking behavior. Crucially, this does not reflect changing preferences but a changing perceptual context. Salience theory thus reframes the Allais paradox as a consequence of a cognitive mechanism rather than evidence of irrationality (Bordalo et al., 2012).

Formally, salience theory replaces the standard independence assumption with context-dependent probability weighting. The salience of a payoff x_{is} of lottery i in state s is measured relative to the average payoff $\bar{x}_s$ across all available lotteries in that state, using the salience function proposed by Bordalo et al. (2012b) and applied empirically by Cosemans and Frehen (2021):

$$\sigma(x_{is}, \overline{x_s}) = \frac{|x_{is} - \overline{x_s}|}{|x_{is}| + |\overline{x_s}| + \theta}$$

where $\theta > 0$ is a small stabilizing constant that prevents zero-payoff states from receiving maximal salience. The salience function satisfies three key properties. First, ordering ensures that salience increases with the absolute distance between a payoff and the average, so that more extreme deviations capture more attention. Second, diminishing sensitivity implies that a given absolute difference becomes less salient when all payoff levels rise uniformly, capturing the intuition that differences in outcomes are perceived less intensely at higher stakes. Third, reflection states that salience depends only on the magnitude of payoffs, not their sign, so gains and losses of equal size are treated symmetrically (Bordalo et al., 2013; Cakici & Zaremba, 2022).

Given this salience function, the salient thinker ranks each lottery's payoffs by their salience, assigning rank $k_{is} = 1$ to the most salient state and $k_{is} = S$ to the least salient. Objective state probabilities π_s are then replaced by salience-distorted decision weights. Within each stock-month, all trading days are initially assumed to occur with equal probability, such that:

$$\pi_s = \frac{1}{S}$$

$$\widetilde{\pi_{is}} = \pi_s \cdot \omega_{is}, \quad \text{where} \quad \omega_{is} = \frac{\delta^{k_{is}}}{\sum_{s'} \delta^{k_{is'}} \cdot \pi_{s'}}$$

The parameter $\delta \in [0,1]$ governs the strength of the distortion. When $\delta = 1$, all states receive equal weight and the investor behaves rationally. As δ decreases below one, more salient states are increasingly overweighted relative to less salient ones, and in the limit as $\delta \to 0$, the decision-maker attends only to the single most salient outcome. The decision weights are normalized so that $E[\omega_{is}] = \Sigma_s \pi_s \omega_{i,s} = 1$, ensuring that they represent distortions around the objective probabilities rather than probabilities themselves. Note that the weights $\omega_{i,s}$ do not necessarily sum to one in an unweighted sense. It is only their probability-weighted expectation that equals one by construction (Cosemans & Frehen, 2021). In the empirical literature, a value of δ = 0.7 has been adopted as the baseline calibration (Bordalo et al., 2012; Cosemans & Frehen, 2021), and this thesis follows the same convention, as detailed in Section 3.2.

This parameterization has an important implication for cross-country applications of salience theory. The parameter δ can be interpreted as a proxy for cognitive ability or, more broadly, for the behavioral characteristics of a given investor population. Populations that are more sensitive to extreme or unusual outcomes, for example due to higher uncertainty aversion or lower risk tolerance, may be associated with a lower effective value of δ, implying stronger salience distortions. This observation motivates the country-specific calibration examined in Section 4.5 of this thesis.

Taken together, salience theory offers a unified framework for understanding why the same individual may exhibit risk aversion in some contexts and risk seeking in others, not because preferences are unstable, but because the relative prominence of outcomes shifts with the comparison set. This context-dependence is the mechanism through which salience generates systematic and predictable patterns in investor behavior.

2.2. Salience in Asset Pricing

The mechanics of salience-based decision-making established in Section 2.1 have direct implications for how risky assets are priced in financial markets. A stock is, in essence, a lottery: it delivers different payoffs in different states of the world, and investors must evaluate it in the context of all available alternatives. Because salience is defined relative to a comparison set, the same distortions that cause individuals to overweight salient outcomes in lottery choices also operate when investors choose between stocks in a market. The key question is how these individual-level distortions aggregate into equilibrium prices and what patterns of return predictability they generate in the cross-section.

2.2.1. The Salience-Based Asset Pricing Model

Bordalo, Gennaioli, and Shleifer (2013) develop a formal model of investor choice and market equilibrium in which salience distortions affect the pricing of risky assets. In their framework, investors evaluate each asset by comparing its payoffs to the average market payoff in each state of the world. The salience of a stock's payoff in a given state therefore depends not on its absolute level, but on how distinctively it deviates from the market benchmark, the same mechanism described in Section 2.1.

Assuming a measure one of identical investors who trade to maximize their expected salience-weighted utility, the equilibrium price of each asset j is (Bordalo et al., 2013):

$$p_j = E[\omega_{js} \cdot x_{js}] = E[x_{js}] + \text{cov}[\omega_{js}, x_{js}]$$

The price of a stock equals the expected value of its future payoff plus a covariance term between its payoffs, and the salience weights investors assign to those payoffs. This second term is the heart of the model. When $\delta = 1$ (the rational benchmark) salience weights are uniformly equal to one across all states, the covariance is zero, and the asset is priced at its fundamental value. When $\delta < 1$, the covariance term introduces a systematic difference between market prices and fundamental values.

The direction of this difference depends on whether salience is concentrated in high or low payoff states. When a stock's highest payoffs are the most salient, when $\text{cov}[\omega_{js}, x_{js}] > 0$, investors overweight the asset's upside potential. Excess demand inflates the price above its fundamental value, generating overvaluation and a negative expected risk premium. Conversely, when a stock's lowest payoffs are most salient, when $\text{cov}[\omega_{js}, x_{js}] < 0$, attention is drawn to downside risk, the asset is underpriced, and investors require a positive risk premium as compensation (Bordalo et al., 2013).

Dividing both sides of the pricing equation by p_j translates this into an expected return prediction. The salience theory value of stock i is defined as (Cosemans & Frehen, 2021):

$$E[r_{is}] = -\text{cov}[\omega_{is}, r_{is}] \equiv -ST_i$$

This is the central testable prediction of the model: stocks with positive ST values, where salient states align with high returns, are overpriced and should earn lower future returns. Stocks with negative ST values, where salient states align with low returns, are underpriced and should earn higher future returns. The empirical analysis in this thesis tests precisely this prediction for the cross-section of German equity returns.

An important feature of the salience-based pricing framework is its reliance on a form of narrow framing. Narrow framing occurs when an agent evaluates a new risk in isolation, separately from the other risks she already faces, rather than merging it with her existing portfolio (Barberis et al., 2006). In traditional models, investors assess each asset solely by its contribution to overall portfolio risk. Under narrow framing, by contrast, investors focus on the payoff distribution of an individual stock independent of their personal wealth or portfolio composition.

In the salience model, this assumption is embedded in the measurement of salience itself: since the salience of a stock's return is determined purely by its deviation from the market average and not by any investor-specific characteristic, all investors perceive the same returns as salient. Consequently, salience-driven demand distortions are correlated across investors and can exert systematic pressure on prices, given limits to arbitrage that prevent rational investors from fully correcting mispricing (Cosemans & Frehen, 2021). This distinguishes the salience mechanism fundamentally from standard risk-based asset pricing models such as the CAPM, in which cross-sectional return differences reflect compensation for systematic risk exposures only.

2.2.2. From Theory to Empirical Measure

To test the model's predictions empirically, the theoretical state space must be operationalized. Investors are assumed to represent each stock's future payoff distribution by its recent daily return history. Each trading day within a month thus defines a state of the world, and all states are assumed to occur with equal objective probability. The salience of each daily return is then measured by comparing the individual stock return to the return on a broad market index on the same day, in this thesis, the value-weighted CDAX total return index, using the salience function introduced in Section 2.1. While the equal-weighted cross-sectional average return serves as benchmark in earlier work (Cosemans & Frehen, 2021), the present analysis adopts a market-index approach, following the international evidence (Cakici & Zaremba, 2022).

This implementation embeds a key intuition from the model: a 5% stock return is considerably more salient on a day when the market is flat than on a day when the market also rises 5%, because what captures investor attention is the relative deviation from the benchmark, not the absolute level of the return (Cosemans & Frehen, 2021). Daily salience scores are then ranked within each stock-month to assign salience weights ω_{is} via the distortion parameter δ. The final monthly salience measure, ST, is computed as the covariance between these salience weights and the corresponding daily returns within each stock-month, directly implementing the theoretical quantity $\mathrm{cov}[\omega_{is}, r_{is}]$ that determines the direction and magnitude of mispricing.

2.3. Limits to Arbitrage and Salience-Driven Mispricing

The salience-based pricing model predicts that attention-driven distortions generate systematic mispricings in the cross-section of stocks. However, for these mispricings to be empirically detectable and exploitable through a trading strategy, they must persist long enough to be measured. This persistence requires that rational investors face obstacles in correcting the mispricing through arbitrage. The theory of limits to arbitrage, developed by Shleifer & Vishny (1997) and extended in subsequent work, provides the necessary complement to behavioral models by explaining why mispricing does not instantaneously self-correct (Cakici & Zaremba, 2022).

Arbitrage in practice is neither riskless nor costless. Rational investors who identify a mispriced security face transaction cost, short-selling constraints, and the risk that the mispricing deepens before it corrects is called arbitrage risk. These frictions are not uniformly distributed across the market: they are systematically more severe for smaller, less liquid, and less transparent firms. Small-cap stocks are associated with higher bid-ask spreads, lower trading volume, reduced analyst coverage, and a smaller supply of lendable shares for short-selling, all of which increase the cost and risk of correcting a mispricing (Brav et al., 2010). High idiosyncratic volatility further compounds arbitrage risk, as the uncertainty surrounding fundamental value makes it harder to determine whether a price deviation reflects mispricing or new information (ZHANG, 2006).

This framework generates a clear prediction that is directly relevant to the present analysis: salience-driven mispricing should be most pronounced, and most persistent, among small and illiquid firms where arbitrage is costly. Cosemans and Frehen (2021) confirm this prediction for the US market, showing that the negative relation between ST and future returns is significantly stronger among small stocks, illiquid stocks, stocks with high idiosyncratic volatility, and stocks with low institutional ownership and analyst coverage. Cakici and Zaremba (2022) reach a similar conclusion in an international sample of 48 countries, finding that the salience anomaly is priced almost exclusively in microcap firms and is absent in small and large firms that together represent 97% of global market capitalization. They describe this as the "Achilles' heel" of the salience effect: its economic significance is real but concentrated precisely where trading frictions are most binding (Cakici & Zaremba, 2022).

2.4. Market-Wide Effects and State-Dependence

Beyond the cross-sectional variation in salience effects across firms, the salience-based asset pricing model also generates predictions about how the strength of salience-driven mispricing varies over time with aggregate market conditions. These time-series predictions arise naturally from the model's structure: because salience is defined relative to the market benchmark, changes in aggregate market payoffs alter the salience of individual stock returns, generating countercyclical variation in risk premia.

In good times, when market payoffs are high, the downside of a risky asset tends to be close to the safe payoff, making the upside salient. Investors overweight the upside, generate excess demand for risky assets, and drive prices above fundamental values. Expected returns consequently fall. In bad times, when market payoffs deteriorate, the risky asset's downside becomes salient relative to the safe asset, leading to underpricing and a positive risk premium. This mechanism implies that the equity premium is countercyclical and that salience-driven overvaluation is concentrated during market upturns (Bordalo et al., 2013).

The empirical literature offers two complementary but partially divergent perspectives on how this time-series variation manifests in practice. Cosemans & Frehen (2021) find that the salience effect in the US is amplified during high-sentiment periods, when unsophisticated and overly optimistic investors are more likely to be active in the market and more prone to engaging in salient thinking. Following the Baker & Wurgler, (2006) sentiment index, the monthly equal-weighted long-short ST portfolio return equals −1.41% in high-sentiment months and −0.88% in low-sentiment months, a statistically significant difference of 53 basis points.

Cakici and Zaremba (2022), by contrast, find in an international sample that the salience anomaly is primarily concentrated in volatile market states and following severe market downturns, rather than high-sentiment periods. Their results show that market-wide volatility, short-term past market returns, and tail risk are the key time-series drivers of salience strategy profits. Elevated volatility worsens funding conditions, raises arbitrage costs, and restricts the activities of sophisticated investors. All of which allow behavioral mispricings to persist for longer. Notably, they find no significant role for the Baker-Wurgler sentiment index in their international sample, in contrast to the US-specific findings of Cosemans and Frehen (2021).

These two perspectives are not necessarily contradictory but reflect differences in sample composition, time horizon, and the institutional characteristics of the markets studied. In the US optimistic sentiment periods may directly amplify salient thinking. In international markets with different investor compositions, including Germany the sentiment channel may be weaker, while arbitrage-cost frictions tied to volatility remain the dominant driver of time-series variation.

Whether the salience effect in Germany more closely follows the volatility-driven pattern of Cakici and Zaremba (2022) or the sentiment-driven pattern of Cosemans and Frehen (2021) is an empirical question that the market state analysis in this thesis directly addresses.

2.5. The German Equity Market and Investor Behavior

The empirical analysis in this thesis focuses specifically on the German equity market, which offers a distinctive institutional and behavioral setting for examining salience-based asset pricing. Understanding the structural and behavioral characteristics of this market is important for two reasons. First, they determine the conditions under which salience-driven mispricing is likely to arise and persist, given the interaction between behavioral biases and limits to arbitrage established in Section 2.3. Second, they motivate the country-specific calibration of the salience distortion parameter examined in Section 4.5, as the behavioral characteristics of German investors may differ systematically from those in the US market where salience theory was originally tested.

2.5.1. Structural Characteristics

The German equity market differs from the US and other major capital markets along several structural dimensions that are relevant to the salience framework. Listed German firms are characterized by higher ownership concentration, with a substantial share of equity held in large, stable blocks by families, corporations, or the state (Finter et al., 2012). This ownership structure reduces the liquidity of many stocks, particularly in the small- and mid-cap segment, and limits the supply of shares available for short-selling. Both are factors that directly raise arbitrage costs and allow mispricing to persist longer, as discussed in Section 2.3. The German market therefore represents a meaningful out-of-sample test of the salience model beyond the US evidence of Cosemans & Frehen (2021) and the international evidence of Cakici & Zaremba (2022), in a setting where structural limits to arbitrage are pronounced.

The predominance of institutional investors in the large-cap segment has a further structural implication. Institutional investors have greater resources for fundamental analysis, lower transaction costs, and more capacity to engage in short-selling, all of which facilitate arbitrage and limit the persistence of mispricing in large, liquid stocks. By contrast, the smaller end of the German market, where analyst coverage is thinner, liquidity lower, and institutional ownership less prevalent, more closely resembles the segments where Cosemans and Frehen (2021) and Cakici and Zaremba (2022) find salience effects to be most pronounced internationally. The German market thus has a dual structure: a large-cap segment where arbitrage conditions are relatively efficient, and a broader small-cap universe where limits to arbitrage are more binding and behavioral effects are more likely to influence prices.

2.5.2. Behavioral Characteristics of German Investors

Beyond structural features, there is evidence that German investors exhibit behavioral characteristics that differ from those in the US and that are directly relevant to the strength of salience distortions. Two sources of cross-country evidence are particularly informative.

The first is Hofstede's cultural dimensions framework, which provides large-scale survey-based evidence on national differences in economic behavior (*The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.). One relevant dimension is uncertainty avoidance, which captures the extent to which individuals in a society feel uncomfortable with ambiguity and unexpected outcomes. Germany scores substantially higher on uncertainty avoidance than the United States. In the context of salience theory, high uncertainty avoidance implies that German investors may react more strongly to return realizations that are extreme, unusual, or conspicuously different from the market average, precisely the outcomes that the salience function assigns high salience scores to. This heightened sensitivity to distinctive outcomes is consistent with a stronger tendency to overweight salient states in the probability distortion process described in Section 2.1.

The second source is the Global Preference Survey (GPS) (Falk et al., 2018), which provides standardized cross-country measures of economic preferences including risk tolerance and patience. Germany has a risk-taking score of −0.044, compared to 0.117 for the United States, indicating that German individuals are on average meaningfully less willing to take risks. Germany's patience score of 0.624 also falls below the US figure of 0.811. Together, these preference measures suggest that the German investor population is characterized by greater caution and sensitivity toward downside outcomes relative to typical US benchmarks.

From the perspective of salience theory, lower risk tolerance and higher uncertainty avoidance point toward a stronger overweighting of salient return realizations. In the framework of Section 2.1, the behavioral intensity of salience distortions is governed by the parameter δ: lower values of δ imply stronger distortions. If German investors systematically overweight salient states more intensely than is captured by the standard calibration of $\delta = 0.7$ derived from the US literature, then a lower value of δ may provide a more behaviorally accurate representation of investor behavior in this market. This reasoning motivates the country-specific recalibration to $\delta = 0.5$ examined in Section 4.5 of this thesis.

2.5.3. Implications for the Present Analysis

Taken together, the structural and behavioral characteristics of the German equity market suggest that it is a suitable but demanding setting for testing salience theory. The market is large enough and sufficiently long-lived to support meaningful empirical analysis across multiple market cycles, yet its features create conditions under which behavioral effects may be present but unevenly distributed across the market.

These characteristics translate directly into a set of testable predictions that structure the empirical analysis of this thesis. First, if salience-driven mispricing is present in the German market, it should be detectable as a negative cross-sectional relation between a stock's ST value and its subsequent return, which is the central prediction of the Bordalo et al. (2013) model. Second, given the dual market structure described above, the effect should be more pronounced among smaller, less liquid firms where limits to arbitrage are more binding, and weaker or absent among large-cap stocks where institutional scrutiny and arbitrage activity are more effective. This prediction implies a meaningful divergence between equally-weighted and value-weighted portfolio results. Finally, the behavioral evidence from Hofstede's cultural dimensions and the Global Preference Survey motivates testing whether a country-specific calibration of the distortion parameter δ provides a better empirical representation of salience distortions among German investors than the standard US-derived parameterization.

These three questions on the existence of the salience effect, its concentration in small firms, and the role of country-specific behavioral calibration define the scope of the empirical investigation that follows.

3. Methodology

This section describes the empirical framework employed to test the predictions of salience theory in the German equity market. Section 3.1 outlines the data sources and sample construction. Section 3.2 details the construction of the salience measure. Sections 3.3 and 3.4 present the portfolio sorting and Fama-MacBeth regression frameworks, respectively, including the control variables specific to each approach.

3.1. Data Collection

The empirical analysis is based on data obtained from Refinitiv Workspace, which provides comprehensive coverage of listed German equities including return histories, market capitalization, trading activity, and firm-level accounting data. Refinitiv has been widely employed in empirical studies of European and German equity markets, including Finter et al. (2012), who use the same data infrastructure for a study of the German stock market. The dataset comprises both daily and monthly stock-level information for German equities, as well as corresponding market index data, which serves as the benchmark in constructing of the salience measure.

The sample consists of publicly listed German firms and spans the period from 1 December 1988 to 29 December 2023. The sample begins on 1 December 1988, corresponding to the earliest date at which the Refinitiv dataset provides complete coverage of German listed equities without gaps in return history for delisted firms. Observations prior to this date are excluded because the dataset does not systematically capture delisting returns for earlier periods, which would introduce survivorship bias by overstating average returns if only surviving firms are retained (Shumway & Warther, 1999).

All return series are denominated in U.S. dollars. This choice ensures methodological comparability with the international salience literature and avoids potential discontinuities in the return series arising from the currency transition between the Deutsche Mark and the Euro in January 2002.

The dataset is constructed from five complementary files obtained from Refinitiv Workspace, linked via a common firm identifier (dscd) and a monthly time identifier (month_id). Daily stock-level data provide the foundation for constructing the salience measure, containing total returns, trading volume, and turnover alongside the value-weighted CDAX total return index, which serves as the market benchmark throughout the analysis. Monthly stock-level data constitute the main panel for portfolio sorts and regressions, containing monthly returns, market capitalization, and the risk-free rate. Firm-level accounting data supply the control variables used in the cross-sectional regressions, including book equity, profitability, and asset-level information. Factor return data provide pre-constructed monthly long-short portfolio returns for the German market, used as benchmarks in the asset pricing tests (Jensen et al., 2023). All return variables are winsorized to mitigate the influence of extreme observations.

3.2. Salience Variable Construction

This study follows the salience framework of Bordalo et al. (2012) and its empirical implementation by Cosemans & Frehen (2021) and Cakici & Zaremba (2022).

In contrast to the original specification, which defines salience relative to the cross-sectional average return, the present analysis adopts a value-weighted market index as the reference point. The present analysis instead uses the value-weighted CDAX total return index as the market benchmark. This choice is motivated by two considerations. First, a broad market index provides a stable and economically interpretable reference point that captures the aggregate market payoff against which individual stock returns are evaluated. Second, prior literature shows that the predictive power of the salience measure is not sensitive to the choice of benchmark weighting scheme, providing empirical support for this modification (Cakici & Zaremba, 2022).

The construction of the salience measure is based on daily stock-level data. The panel is sorted by firm and trading day, and the uniqueness of the stock-day dimension is verified. This step guarantees that each observation corresponds to a distinct firm-day combination, which is a necessary condition for the correct computation of daily salience measures.

The daily salience of stock returns is computed following Cakici & Zaremba (2022). For each stock i on trading day s, salience is defined as the normalised distance between the individual stock return and the market benchmark:

$$\sigma_{i,s} = \frac{\mid r_{i,s} - r_s \mid}{\mid r_{i,s} \mid + \mid r_s \mid + \theta}$$

where $r_{i,s}$ denotes the daily return of stock i, and r_s represents the value-weighted market return on day s, proxied by the CDAX total return index.

As established in Section 2.1, the salience function satisfies the properties of ordering, diminishing sensitivity, and reflection, ensuring that the measure captures the relative distinctiveness of payoffs in a manner consistent with behavioral decision theory.

The parameter θ is set to 0.1, in line with the existing literature. This parameter ensures numerical stability and governs the sensitivity of the salience function to differences in returns. Economically, the measure captures the extent to which a stock's payoff stands out relative to the market benchmark. Larger deviations from the market return lead to higher salience values, reflecting the idea that investors overweight outcomes that are particularly distinctive in a given context.

In the empirical implementation, salience is computed using winsorized daily returns to mitigate the influence of extreme observations. Specifically, the numerator is defined as the absolute deviation between the individual stock return and the market return, while the denominator normalizes this deviation by the sum of absolute returns and the constant θ. The resulting salience measure is bounded between zero and one and varies across stocks and time.

Descriptive statistics for the daily salience measure $\sigma_{i,s}$ indicate substantial cross-sectional and time-series variation, with a mean of approximately 0.13 and a maximum value close to one (see Appendix, Table 7-1). These daily values form the basis for the subsequent ranking and aggregation to the stock-month level.

For each stock i and month t, all daily salience values $\sigma_{i,s}$ are ranked in descending order. The most salient observation within a given stock-month is assigned rank $k_{i,s} = 1$, while the least salient observation receives rank $k_{i,s} = S$, where S denotes the number of trading days in that month. This ranking procedure defines the state space of possible outcomes and captures the relative importance of each daily return realization within the stock-specific payoff distribution.

Following the theoretical framework established in Section 2.1, objective state probabilities are transformed into salience-weighted subjective probabilities using the distortion parameter $\delta = 0.7$, in line with the existing literature (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021).

In the final step, the salience measure is aggregated to the stock-month level. The salience of a stock is defined as the covariance between salience weights and realized returns within each estimation period (Cosemans & Frehen, 2021). Specifically, for each stock i and month t, the salience measure is computed as:

$$ST_{i,t} = \mathrm{cov}(\omega_{i,s}, r_{i,s}),$$

where $\omega_{i,s}$ denotes the salience weight and $r_{i,s}$ the daily return of stock i on day s within month t (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021). This measure captures whether highly salient return realizations coincide with relatively high or low returns. A positive value of $ST_{i,t}$ indicates that salient states are associated with high returns, implying that investor attention is concentrated on positive

outcomes. Conversely, a negative value suggests that salient states coincide with low returns, indicating that attention is directed toward negative outcomes.
Economically, this distinction is crucial. If salient days align with high returns, this may lead to overvaluation and consequently, lower future returns. In contrast, if salient days align with low returns, this may reflect underpricing and predict higher subsequent returns. Thus, cross-sectional variation in the salience measure captures differences in how attention is allocated across assets and serves as the basis for the empirical analysis in later sections.
Specifically, the covariance between salience weights and daily returns is calculated across all trading days within a given month. As a result, the salience measure is constant within each stock-month and varies only across stocks and over time. Descriptive statistics indicate that the salience measure is centered close to zero, with a slightly positive mean and substantial dispersion across observations. This is consistent with the properties of a covariance measure: $ST_{i,t}$ averages to zero across stocks and time by construction, as positive and negative values cancel out in the cross-section. This does not imply the absence of salience-driven mispricing. Rather, the empirical predictions of salience theory concern the cross-sectional dispersion of ST, with high-ST stocks expected to earn lower returns than low-ST stocks. At the same time, the presence of both positive and negative values, as well as meaningful variation in magnitude, ensures sufficient cross-sectional heterogeneity for subsequent portfolio sorting and regression analyses (see Appendix, Table 7-2 and 7-3).

3.3. Portfolio Sorts

To evaluate the economic relevance of the salience effect, this study employs portfolio-sorting techniques. Instead of imposing a specific functional form, such as a linear relationship between salience and returns, portfolio sorts group stocks into portfolios based on their characteristics and compare their subsequent performance. This methodology allows for a transparent assessment of whether systematic differences in returns exist across stocks with varying levels of salience.
Portfolio-sorting procedures provide an intuitive economic interpretation, are robust to outliers, and enable the detection of monotonic patterns in the cross-section of returns (Fama & French, 1992). In particular, they allow testing whether returns increase or decrease systematically across characteristic-sorted portfolios and whether the return spread between extreme portfolios is economically meaningful.

3.3.1. Control Variables

To isolate the effect of the salience-based measure on stock returns, it is necessary to control for well-established risk factors documented in the empirical asset pricing literature (Fama & French, 1992, 2015; Jegadeesh & Titman, 1993). To account for these effects, this study incorporates the classical six-factor specification, consisting of the market, size, value, momentum, profitability and investment factors. The factor returns are obtained from the "all_factors" dataset, which provides pre-constructed monthly long-short portfolio returns for a broad set of anomaly-based characteristics in the German equity market. For each factor, the corresponding variable is selected based on its theoretical interpretation and empirical relevance, ensuring consistency with the canonical asset pricing framework (Jensen et al., 2023).
Factors return series are aligned to the monthly panel using a common time identifier and merged with the stock-level dataset at the monthly frequency. This procedure assigns the same set of factor realizations to all stocks within a given month. The resulting dataset provides the necessary structure for subsequent regression analysis, allowing the estimation of the salience-based effect while controlling for established risk factors in a consistent empirical framework.

The size factor (SMB, Small Minus Big) captures the empirical regularity that stocks of small firms tend to outperform those of large firms on average (Banz, 1981; Fama & French, 1992). This effect is commonly

attributed to differences in risk exposure, information asymmetry and market frictions affecting smaller firms. In the present analysis, firm size is proxied by the variable *market_equity*, which measures market capitalization and represents the underlying sorting characteristic for the size factor.
The value factor (HML, High Minus Low) reflects the tendency of firms with high book-to-market ratios to outperform growth firms with low book-to-market ratios (Fama & French, 1992).This pattern is often interpreted as compensation for distress risk or behavioral mispricing. The value dimension is captured using the variable *be_me*, defined as the ratio of book equity to market equity, which corresponds directly to the standard book-to-market measure in the literature.
The momentum factor (MOM or WML, Winner Minus Loser) captures the well-documented phenomenon that stocks with high past returns continue to outperform those with low past returns over intermediate horizons (Jegadeesh & Titman, 1993). Momentum is proxied using the variable *ret_12_1*, which measures cumulative returns over the past twelve months excluding the most recent month, consistent with the standard momentum definition.
The profitability factor (RMW, robust minus weak) reflects the empirical finding that firms with high operating profitability earn higher average returns than firms with low profitability (Fama & French, 2015). Profitability is captured using the variable *ope_be*, defined as operating profits scaled by book equity, which directly corresponds to the measure used in the Fama-French five-factor model.
The investment factor (CMA, Conservative Minus Aggressive) captures the empirical finding that firms with low investment rates tend to outperform firms with high investment rates (Fama & French, 2015). Investment is proxied using the variable *at_gr1*, which measures asset growth and thus reflects firms' investment intensity.
The market factor (MKT) captures the overall systematic risk of the equity market and represents the excess return of the market portfolio over the risk-free rate (Lintner, 1965; Sharpe, 1964). Unlike the other factors, the market factor is not sourced from the all_factors dataset but is instead constructed directly from the CDAX total return index, net of the risk-free rate. This approach ensures that the market benchmark is consistent with the value-weighted CDAX index used as the reference point in the salience measure construction, thereby maintaining internal consistency across the empirical design.

3.3.2. Equally-Weighted

In the first step, the salience measure is lagged by one month so that portfolio formation is based exclusively on information available at the end of the previous month. This timing structure avoids look-ahead bias and ensures that the empirical design tests the predictive power of salience for future stock returns. It preserves the economic interpretation of predictors as ex ante signals available to investors at the time of portfolio formation (Fama & French, 1992).
To examine the economic magnitude of the salience effect, stocks are sorted at the beginning of each month into quintile portfolios based on their lagged salience values. Quintile 1 contains stocks with the highest salience, while quintile 5 comprises stocks with the lowest salience. The resulting portfolios are approximately equally sized, with minor deviations arising from ties in the salience measure and variation in the number of available stocks across months. This sorting procedure enables a direct comparison of subsequent returns across different levels of prior salience. Equally-weighted portfolio returns are computed by averaging the returns of all stocks within each quintile. The use of equal weighting ensures that each stock contributes equally to portfolio performance, thereby preventing large firms from dominating the results (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021).
The zero-investment long-short strategy is formed by taking a long position in the highest salience portfolio (quintile 1) and a short position in the lowest salience portfolio (quintile 5). Consistent with the theoretical prediction that high-salience stocks are temporarily overpriced, this strategy is expected to earn negative returns: if salience-driven mispricing is present, high-salience stocks will underperform low-salience stocks in subsequent periods (Cosemans & Frehen, 2021).

To assess the statistical significance of the long-short portfolio returns, time-series regressions of portfolio returns on a constant are estimated. This approach corresponds to testing whether the average return of the portfolio differs significantly from zero. Because portfolio returns are observed as monthly time series and may exhibit serial correlation and heteroskedasticity, statistical inference is based on Newey-West adjusted standard errors. This applies both to the constant-only regressions used to test average long-short returns and to the factor regressions used to estimate risk-adjusted alphas (Newey & West, 1987). Summary statistics for the equally weighted long-short portfolio are reported in Appendix (Table 7-4).
To evaluate whether the return differential associated with salience is driven by exposure to established risk factors, time-series regressions of the long-short portfolio returns on standard asset pricing factors are conducted. Specifically, the excess return of the salience-based portfolio is regressed on the market factor (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA), following the augmented Fama-French framework (Fama & French, 2015; Jegadeesh & Titman, 1993).
The regression specification is given by:

$$LS_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 RMW_t + \beta_6 CMA_t + \varepsilon_t$$

where LS_t denotes the return of the long-short portfolio in month t. The intercept α captures the abnormal return that is not explained by the included risk factors and thus serves as a measure of the strategy's risk-adjusted performance (Cakici & Zaremba, 2022).
To assess whether the return spread between high- and low-salience stocks can be explained by standard risk factors, a time-series regression of the equally weighted long-short portfolio (LS_ew) on the Fama-French six-factor model is conducted.

3.3.3. Value-Weighted

To account for differences in firm size, value-weighted portfolios are constructed in addition to equal-weighted portfolios. Within each salience quintile, stocks are weighted by their lagged market capitalization, ensuring that portfolio weights reflect the relative economic importance of firms at the time of portfolio formation. The use of lagged market capitalization avoids look-ahead bias and guarantees that weights are predetermined. Portfolio returns are then calculated as the weighted average of individual stock returns within each quintile. As in the equally-weighted specification, statistical inference is based on Newey-West adjusted standard errors (Newey & West, 1987). This specification allows assessing whether the salience effect persists among larger firms or is primarily driven by smaller stocks. Summary statistics for the value-weighted long-short portfolio are reported in Appendix (Table 7-5).
To examine whether the salience-based return pattern persists after accounting for firm size, a time-series regression of the value-weighted long-short portfolio (LS_vw) on the Fama-French six-factor model is conducted. In contrast to the equally weighted specification, this approach assigns greater importance to large-cap firms and therefore provides insight into the economic relevance of the effect for investable portfolios.
To further examine the size distribution of salience-sorted portfolios, Table 7-6 in the Appendix reports the average market capitalization across salience quintiles. The high-salience quintile (Q1) exhibits substantially lower average market capitalization than the remaining quintiles under equal weighting, confirming that salience-based sorting induces a systematic size tilt. This pattern highlights that salience-based portfolios are not size-neutral and motivates the use of both equally weighted and value-weighted specifications. While equal weighting ensures that smaller firms receive comparable importance, value weighting assigns greater weight to larger firms, thereby allowing the analysis to account for potential size-related effects in portfolio returns. To directly test whether the salience effect is concentrated among smaller firms, an additional size-split analysis is conducted. Stocks are classified monthly into two groups

based on cumulative market capitalization: a small-cap group comprising the bottom 10% of total market capitalization, and a large-cap group comprising the remaining 90% (Cakici & Zaremba, 2022). Quintile portfolio sorts are then performed separately within each size group. The results, reported in Table 7-7 in the Appendix.

3.4. Fama-MacBeth Regression Framework

The Fama-MacBeth (1973) two-step procedure is employed to test whether the salience measure retains explanatory power after controlling for established determinants of stock returns. In the first step, a separate cross-sectional regression is estimated for each month. In the second step, the estimated monthly slope coefficients are averaged over time, yielding the mean risk premium associated with each explanatory variable. Section 3.4.1 describes the baseline cross-sectional specifications and Section 3.4.2 introduces the market state framework.

3.4.1. Cross-Sectional Predictive Regressions

Following the portfolio sort analysis, the predictive content of the salience measure is further examined in a regression-based setting. The present study employs the Fama-MacBeth cross-sectional regression framework, which allows the marginal effect of salience on future stock returns to be estimated while simultaneously controlling for established return predictors. This approach therefore complements the portfolio sorts by providing a stricter multivariate test of whether salience retains explanatory power in the cross-section of returns (Fama & MacBeth, 1973).

A central feature of the empirical design is that all explanatory variables are measured in month t, whereas the dependent variable is the stock return realised in month $t + 1$. This timing convention ensures that the regression tests a predictive relation. In other words, the analysis examines whether salience and the control variables, as observed at the end of month t, contain information about future cross-sectional return differences in the subsequent month. Therefore, the dependent variable is constructed as the one-month-ahead stock return by shifting the return series forward within each firm. Observations for which no subsequent return is available are excluded from the analysis.

In each month t, the following cross-sectional regression is estimated across all stocks i:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{ST,t} ST_{i,t} + \sum_{j=1}^{n} \gamma_{K_j,t} K_{i,t}^{j} + \varepsilon_{i,t},$$

where $R_{i,t+1}$ denotes the return on stock i in month $t + 1$, $ST_{i,t}$ is the salience measure observed in month t, and $K_{i,t}^{j}$ represents the set of control variables included in the regression. The coefficient $\gamma_{ST,t}$ captures the cross-sectional relation between salience and subsequent stock returns in month t, conditional on the other explanatory variables (Cakici & Zaremba, 2022).

To control for well-established cross-sectional return determinants, firm-level characteristics are incorporated into the regression framework. In contrast to factor returns, which capture systematic risk premia over time, the Fama-MacBeth approach requires firm-specific variables that vary across stocks within a given month. Accordingly, the analysis includes standard firm characteristics such as size, value, profitability, investment and short-term reversal, which have been shown to explain cross-sectional differences in expected stock returns (Fama & French, 2015; Jegadeesh & Titman, 1993). These variables are constructed from accounting data and merged with the monthly stock-level dataset prior to estimation.

Firm size is measured as the logarithm of market capitalization, which compresses the right-skewed distribution and is standard in the cross-sectional asset pricing literature (Fama & French, 1992). Smaller firms tend to earn higher average returns, and controlling for size ensures that the salience effect is not driven by this well-documented pattern. To reduce the influence of extremely small and illiquid firms prone to microstructure noise, observations with market capitalization below $1 million are excluded from the sample. Given the single-country setting of this study, a market capitalization threshold provides a more stable and economically interpretable screening criterion than a share price filter, which is more common in multi-country studies (Cakici & Zaremba, 2022; Hou et al., 2011).

The book-to-market ratio is defined as book equity divided by market equity and controls for the value premium, which reflects the tendency of high book-to-market firms to outperform growth firms (Fama & French, 1992). As reported in the Appendix (Tables 7-8 and 7-11), the variable is extremely right-skewed prior to winsorization. It is therefore winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations arising from very small market capitalization values.

Profitability captures how efficiently a firm generates earnings relative to its asset base, which is the Return on Assets (ROA). More profitable firms are often systematically different from less profitable firms in terms of expected returns. Therefore, profitability is included as a control variable to ensure that the estimated effect of salience is not driven by differences in operating performance. Profitability is winsorized at the 5th and 95th percentiles to further reduce the influence of extreme accounting observations, which are common in large-scale financial datasets due to reporting inconsistencies and small denominators (see Appendix, Table 7-9 and 7-11).

The investment variable captures how strongly a firm expands its asset base over time. In empirical asset pricing, firms with high investment rates tend to exhibit lower subsequent returns compared to firms with low investment rates. This pattern is commonly referred to as the investment effect and is included as a control to ensure that the estimated salience effect is not driven by differences in corporate investment behavior (Fama & French, 2015). It measures how much the firm expanded its assets relative to the last period. The variable is winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations (see Appendix, Table 7-10 and 7-11).

Short-term reversal (REV) is defined as the stock's return in the prior month, measured as the return lagged by one period. Prior research documents a well-known tendency for stocks to reverse over short horizons (Jegadeesh & Titman, 1993). More importantly, the ST measure is constructed from recent daily return realizations, which creates a mechanical overlap with past monthly returns. Including REV as a control variable therefore directly addresses the concern that the salience effect may partly reflect return reversal rather than attention-driven mispricing. REV is included only in the most comprehensive specification to isolate its incremental effect on the salience coefficient.

The Fama-MacBeth (1973) procedure consists of estimating cross-sectional regressions in each period and then averaging the estimated coefficients over time. This approach allows for the estimation of the average relationship between firm characteristics and expected returns while accounting for time variation in the cross-section.

The final regression sample is obtained by excluding observations with missing values in the dependent variable or any explanatory variable. This results in a reduced but consistent sample, reflecting the limited availability of accounting data, particularly for variables such as book equity. This is to ensure that all regressions are estimated on a comparable set of firm characteristics. Summary statistics and pairwise correlations of the main variables are reported in Appendix (Tables 7-12 and 7-13). The variables exhibit substantial variation across firms and over time, providing a suitable basis for cross-sectional analysis. The correlation matrix indicates that the explanatory variables are not excessively correlated, suggesting that multicollinearity is unlikely to materially affect the regression estimates.

It should be noted that the regression sample differs from the portfolio sort sample, as observations with missing values in any explanatory variable are excluded. This results in a reduced sample that is tilted towards larger, more established firms with complete accounting data. The portfolio sorts, which require only return and salience data, are therefore estimated on a broader sample. This difference should be kept in mind when comparing results across the two empirical approaches.

3.4.2. Market States

To account for time variation in investor beliefs and market conditions, the empirical framework incorporates market state variables. While the baseline specification assumes that the predictive effect of salience is constant over time, behavioral theories suggest that the strength of attention-driven mispricing may depend on prevailing economic environments. In particular, periods of heightened uncertainty or pessimism may amplify investor biases, whereas more stable conditions may attenuate them (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021).

To capture this potential state dependence, the analysis employs two complementary approaches. First, a discrete portfolio-sorting framework compares the performance of long-short salience strategies across different market regimes. Second, a continuous regression specification tests whether variation in market conditions systematically explains changes in the salience premium.

Market conditions are proxied using two measures. The VDAX index serves as an indicator of aggregate market uncertainty, while the SAFE Manager Sentiment Index captures managerial expectations. Both variables are lagged by one month to ensure that they reflect information available at the time of portfolio formation, thereby avoiding look-ahead bias.

Based on these lagged variables, market states are defined using median splits, classifying months into high and low volatility as well as high and low sentiment regimes. This classification enables a comparison of salience portfolio performance across distinct economic environments. The median split approach is a standard but conservative classification method. It assumes a regime change at the median and may not capture the concentration of the salience effect in the most extreme market conditions (Cakici & Zaremba, 2022). A continuous regression framework complements the discrete analysis and partially addresses this limitation. In parallel, time-series regressions of long-short portfolio returns on lagged market state variables provide a continuous test of state dependence.

It should be noted that the VDAX is available from 2001 and the SAFE Manager Sentiment Index from 2003 onwards, such that the market state analysis covers a shorter period than the full sample used in the portfolio sorts and Fama-MacBeth regressions. This difference in sample coverage should be kept in mind when interpreting the market state results.

3.4.2.1. SAFE Manager Sentiment Index

The sentiment measure used in this context is the SAFE Manager Sentiment Index, a monthly indicator that quantifies managerial beliefs by extracting sentiment from corporate financial disclosures, including annual and quarterly reports as well as earnings conference call transcripts. The index is constructed using a dictionary-based textual analysis approach, where the relative frequency of positive and negative words is computed for each document. Sentiment measures derived from financial statements and conference calls are aggregated and combined into a composite index, defined as the equally weighted average of both components. To ensure a consistent monthly frequency despite the quarterly nature of disclosures, the index is calculated as a three-month moving average weighted by the number of available documents. Importantly, the index captures managers' assessment of past firm performance as well as their expectations regarding future developments, thereby providing a forward-looking measure of corporate sentiment (Fadavi & Hillert, n.d.).

To distinguish between different sentiment regimes, a binary market state indicator is constructed using a median split of the lagged index. Months in which the lagged index exceeds its sample median are classified as high-sentiment periods, while the remaining months are classified as low-sentiment periods.

3.4.2.2. VDAX

To capture time-varying market conditions, this study employs the VDAX as a proxy for aggregate market uncertainty in the German equity market. The VDAX, formerly known as VDAX-NEW, reflects the implied volatility of the DAX index derived from option prices and represents the market's expectation of future volatility over a 30-day horizon. Specifically, the index is calculated using both at-the-money and out-of-the-money DAX option contracts with a remaining maturity of approximately 30 days, thereby incorporating forward-looking information embedded in derivatives markets. As implied volatility tends to be negatively correlated with stock market performance, elevated VDAX levels are interpreted as periods of heightened market uncertainty and increased risk aversion, whereas low VDAX levels indicate more stable and optimistic market conditions (*VDAX*, n.d.). Daily observations of the index are obtained from Investing.com and subsequently aggregated to the monthly frequency to align with the empirical asset pricing framework.

To distinguish between different market environments, the monthly VDAX series is transformed into a binary market state indicator using a median split of its lagged value. Months in which the lagged VDAX exceeds its sample median are classified as high-volatility (pessimistic) periods, while the remaining months are classified as low-volatility (optimistic) periods.

Taken together, the SAFE Manager Sentiment Index and the VDAX provide two distinct but complementary perspectives on market conditions: the former captures managerial expectations, while the latter reflects uncertainty priced in financial markets. This distinction allows assessing whether the salience effect varies with different dimensions of aggregate beliefs and uncertainty.

4. Results

This section presents the empirical findings of the analysis. It first examines the economic magnitude of the salience effect using portfolio-sorting techniques, followed by factor-adjusted performance tests. The predictive power of salience is then evaluated in a cross-sectional regression framework. Finally, the analysis explores whether the salience effect varies across different market states, and whether a Germany-specific recalibration of the salience distortion parameter alters the main conclusions.

4.1. Portfolio Sorts

The portfolio sort results are reported separately for equally-weighted and value-weighted specifications. This distinction is central to the analysis, as it allows assessing whether the salience effect is uniformly present across firm sizes or primarily concentrated among smaller stocks.

4.1.1. Equally-Weighted

The results of the portfolio sorts reveal a pronounced and statistically significant salience effect. The long-short portfolio, which takes a long position in the most salient stocks (quintile 1) and a short position in the least salient stocks (quintile 5), yields an average return of −1.15% per month. This return differential is statistically significant, with a Newey-West adjusted t-statistic of −5.35, providing evidence against the null hypothesis of zero abnormal returns (see Appendix, Table 7-14). The negative sign implies that stocks with higher salience underperform those with lower salience in subsequent periods.

Risk-Adjusted Returns of the Long–Short Portfolio (Equal-Weighted)

	Coefficient	Std. Error	t-statistic	p-value
Alpha (α)	-0.0101	0.00234	-4.32	0.000
MKT	0.0813	0.0503	1.62	0.106
SMB	-0.0493	0.1121	-0.44	0.661
HML	-0.3943	0.1687	-2.34	0.020
MOM	-0.0353	0.0773	-0.46	0.648
RMW	-0.2452	0.1225	-2.00	0.046
CMA	0.0874	0.1125	0.78	0.438

Notes: This table reports results from a time-series regression of the equal-weighted long–short portfolio (LS_ew) on the Fama–French five factors and the momentum factor. Newey–West standard errors with one lag are used. The intercept (α) represents the risk-adjusted abnormal return.

Source: Own Analysis

Table 4-1: Risk-Adjusted Returns of the Long-Short Portfolio (Equally-Weighted)

The significant negative alpha ($\alpha = -0.0101$, $t = -4.32$) confirms that the salience-based long-short strategy generates abnormal returns that persist after controlling for the six standard risk factors. This result is the central finding of the EW analysis: the salience effect is not subsumed by common return drivers and may reflect a distinct behavioral source of return predictability.

Turning to the factor loadings, the market factor (MKT) exhibits a positive but statistically insignificant coefficient ($\beta = 0.0813$, $p = 0.106$), indicating no robust directional exposure to overall market movements. The size factor (SMB), momentum (MOM), and investment (CMA) factors all display insignificant loadings, suggesting that these dimensions do not systematically explain the variation of the long-short portfolio.

Two factor loadings warrant particular attention. The value factor (HML) shows a negative and statistically significant loading ($\beta = -0.3943$, $p = 0.020$), indicating that the long leg of the strategy, which are the most salient stocks, tilts toward growth rather than value firms. This is theoretically meaningful: salience theory predicts that growth stocks, which tend to have large salient upsides relative to the market, attract disproportionate investor attention and become overpriced (Bordalo et al., 2013). The negative HML exposure thus independently confirms the behavioral mechanism at the heart of the analysis. The profitability factor (RMW) also carries a negative and statistically significant coefficient ($\beta = -0.2452$, $p = 0.046$), implying that the strategy is negatively exposed to firms with robust profitability. This pattern is consistent with lottery-type stocks, where low-profitability firms' upside receives disproportionate attention, being concentrated in the high-salience quintile (Bordalo et al., 2013; Cosemans & Frehen, 2021).

4.1.2. Value-Weighted

To assess whether the salience effect persists among larger and more economically important firms, portfolios are also constructed using value-weighted returns. This approach assigns greater weight to large-cap stocks and thereby provides a more direct test of whether the effect extends to larger, more liquid stocks that are more accessible to investors.

The long-short portfolio yields an average return of approximately -0.34% per month, which is substantially smaller in magnitude compared to the equal-weighted specification. Critically, this return is not statistically significant, with a Newey-West adjusted t-statistic of -1.27 (see Appendix, Table 7-15). The null hypothesis that the average return equals zero cannot be rejected at conventional significance levels. The contrast with the EW result is stark and constitutes one of the central structural findings of this paper: the salience effect in the German equity market is concentrated among smaller firms and does not translate into statistically meaningful abnormal returns once larger firms receive proportionally greater weight.

Risk-Adjusted Returns of the Long–Short Portfolio (Value-Weighted)

	Coefficient	Std. Error	t-statistic	p-value
Alpha (α)	-0.00109	0.00267	-0.41	0.682
MKT	0.0767	0.0756	1.01	0.311
SMB	0.0195	0.1618	0.12	0.904
HML	-0.5929	0.1922	-3.08	0.002
MOM	-0.2705	0.1086	-2.49	0.013
RMW	-0.1897	0.1606	-1.18	0.238
CMA	0.4200	0.1532	2.74	0.006

Notes: This table reports results from a time-series regression of the value-weighted long–short portfolio (LS_vw) on the Fama–French five factors and the momentum factor. Newey–West standard errors with one lag are used. The intercept (α) represents the risk-adjusted abnormal return.

Source: Own Analysis

Table 4-2: Risk-Adjusted Returns of the Long-Short Portfolio (Value-Weighted)

The factor regression validates this interpretation. The alpha is economically negligible and statistically insignificant ($\alpha = -0.0011$, $t = -0.41$), confirming that the salience-based abnormal return disappears in the value-weighted specification after controlling for standard risk factors. The included factors jointly explain a meaningful portion of the variation in VW long-short portfolio returns, in contrast to the EW specification where factor exposure was largely absent. This itself reveals that the VW portfolio's return dynamics are better described by systematic risk exposures than by a residual behavioral component.

Regarding the individual factor loadings, the value factor (HML) remains strongly negative and statistically significant ($\beta = -0.5929$, $p = 0.002$), reinforcing the growth-tilt already documented in the EW case. The momentum factor (MOM) exhibits a negative and significant loading ($\beta = -0.2705$, $p = 0.013$), suggesting that the strategy is negatively exposed to past winners in the large-cap space. Most notably, the investment factor (CMA) shows a positive and statistically significant loading (β = 0.4200, p = 0.006), which was absent in the EW regression. This indicates that large-cap stocks driving the VW portfolio returns tend to be firms with conservative investment policies, a dimension of cross-sectional variation that is irrelevant among the small-cap stocks that dominate the EW portfolio. The market factor (MKT), size factor (SMB), and profitability factor (RMW) remain statistically insignificant.

The size-split analysis reported in the Appendix (Tables 7-6 and 7-7) confirms this interpretation: the long-short portfolio yields −1.32% per month among small-cap stocks (t = -6.07, α = -1.24%), while the effect is economically negligible and statistically insignificant among large-cap firms.

Taken together, the EW and VW results reveal a consistent pattern: the salience effect in Germany is real and significant among smaller firms but is not reflected in returns once larger, more liquid stocks receive proportionally greater weight. Section 4.2 examines whether the negative relation between salience and future returns persists after controlling for firm characteristics in a multivariate regression framework.

4.2. Fama-MacBeth Regressions

This section presents the results of the Fama-MacBeth (1973) cross-sectional regressions, which examine whether the salience measure predicts future stock returns after controlling for standard firm characteristics. The dependent variable is the stock return in month $t + 1$, while all explanatory variables are measured at time t, ensuring a predictive setting and avoiding look-ahead bias. To assess the incremental predictive content of salience, the regressions are estimated in nested specifications, beginning with salience alone and sequentially adding firm size, book-to-market, profitability, investment, and short-term reversal. This stepwise approach makes it possible to observe whether the estimated salience premium is robust to the inclusion of established cross-sectional return predictors.

Fama-MacBeth Regressions of Future Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: r_{t+1}					
ST	-0.1595***	-0.1672***	-0.1589***	-0.1636***	-0.1688***	-0.1823***
	(0.0286)	(0.0284)	(0.0280)	(0.0273)	(0.0267)	(0.0264)
Size		-0.0010***	-0.0003	-0.0013***	-0.0013***	-0.0012***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
BM			8.7381***	8.0271***	7.9978***	8.2740***
			(0.8367)	(0.7885)	(0.7890)	(0.7781)
ROA				0.0010***	0.0010***	0.0010***
				(0.0001)	(0.0001)	(0.0001)
Asset Growth					-0.4965	-0.7069
					(0.5556)	(0.5932)
REV						-0.0002
						(0.0051)
Constant	0.0093***	0.0144***	0.0040	0.0077***	-0.0093	-0.0119
	(0.0028)	(0.0031)	(0.0030)	(0.0028)	(0.0121)	(0.0122)
Observations	220,415	220,415	220,415	220,415	220,415	216,037
Time periods	420	420	420	420	420	419
Avg. R^2	0.0100	0.0200	0.0275	0.0424	0.0462	0.0537

Notes: This table reports Fama–MacBeth (1973) cross-sectional regressions of future stock returns (r_{t+1}). Newey–West corrected standard errors with one lag are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own Analysis

Table 4-3: Fama-MacBeth Regressions of Future Returns

The results provide strong and consistent evidence that salience is negatively related to future stock returns. In the univariate specification (1), the coefficient on the salience variable is −0.1595 and significant at the 1% level, indicating that stocks with higher salience exhibit significantly lower subsequent returns. This finding is consistent with the core prediction of salience theory: investors overprice salient stocks, leading to lower future returns (Bordalo et al., 2012, 2013).

The negative effect of salience remains robust across all subsequent specifications. After controlling for firm size in specification (2), the coefficient becomes slightly more negative (−0.1672, significant at the 1% level), indicating that the salience effect is not driven by differences in firm size. The inclusion of book-to-market, profitability, and investment in specifications (3) through (5) does not materially alter the magnitude or statistical significance of the salience coefficient, which remains at −0.1688 (significant at the 1% level). This stability suggests that salience captures a distinct dimension of expected returns that is not subsumed by standard firm characteristics.

Specification (6) additionally controls for short-term reversal (REV), defined as the lagged one-month return. The salience coefficient strengthens slightly to −0.1823 (significant at the 1% level), while REV itself is statistically insignificant.

The control variables generally exhibit signs consistent with the established asset pricing literature. Firm size enters with a negative and significant coefficient, consistent with the size effect (Fama & French, 1992). Book-to-market is positive and highly significant, confirming the value premium. Profitability shows a positive relationship with future returns (Novy-Marx, 2013). In contrast, asset growth is statistically insignificant in the full specification, suggesting it does not contribute additional explanatory power in the present sample.

Overall, the Fama-MacBeth results provide compelling cross-sectional evidence that salience has significant and economically meaningful predictive power for future stock returns in Germany. The salience premium is robust to a comprehensive set of firm-level controls and is not explained by return reversal, supporting the interpretation that it reflects a distinct behavioral component of the cross-section of expected returns.

4.3. Market States

This section presents the empirical results on the state dependence of the salience effect. Building on the methodology outlined in Section 3.4.2, the performance of long-short salience portfolios is evaluated across different market environments using both discrete portfolio sorts and continuous regression specifications.

The Salience Effect in Different Market States

	Equal-weighted portfolios		Value-weighted portfolios	
	$\bar{R}$	α	$\bar{R}$	α
Panel A: Volatile versus stable markets				
High market volatility	-1.71		0.14	
Low market volatility	-1.12		-0.77	
High − Low	-0.59	-0.46	0.91	0.68
		(-0.80)		(0.98)
Panel B: High versus low sentiment markets				
High sentiment	-0.91		-0.25	
Low sentiment	-1.57		-0.26	
High − Low	0.66	0.68	0.01	0.06
		(1.39)		(0.10)

Notes: This table reports average monthly returns ($\bar{R}$) and risk-adjusted alphas (α) of long–short salience portfolios across different market states. Panel A splits the sample based on median market volatility, while Panel B splits the sample based on median market sentiment. High − Low denotes the difference between the respective states. Alphas are estimated using the Fama–French five factors and momentum. Newey–West t-statistics with one lag are reported in parentheses.

Source: Own Analysis

Table 4-4: The Salience Effect in Different Market States

Table 4-4 reports the performance of the long-short salience portfolios conditional on market states defined by lagged volatility and sentiment.

For equal-weighted portfolios, the salience strategy yields negative returns across both market environments, indicating a persistent effect. In Panel A, the magnitude is somewhat stronger during high-volatility periods (−1.71%) than low-volatility periods (−1.12%). However, the High-Low spread of -0.59% is not statistically significant.

Panel B reveals a more notable finding: the salience effect is stronger during low-sentiment periods (-1.57%) than high-sentiment periods (−0.91%). That said, the High-Low difference of 0.66% remains statistically insignificant, so the result is directional rather than conclusive. For value-weighted portfolios, conditioning on either volatility or sentiment yields negligible and statistically insignificant variation across regimes.

Market States and the Dynamics of the Salience Effect

	Equal-weighted portfolios		Value-weighted portfolios	
	No controls	FF6 controls	No controls	FF6 controls
Lagged volatility (VDAX)	-0.073	-0.075	-0.066	-0.067
	(-1.39)	(-1.38)	(-1.04)	(-1.09)
Lagged sentiment (SAFE)	-0.012	-0.013	-0.779	-0.664
	(-0.04)	(-0.05)	(-1.85)	(-1.58)
Controls (FF6)	No	Yes	No	Yes
Observations	214	214	214	214

Notes: This table reports time-series regressions of long–short salience portfolio returns on lagged market state variables. Lagged volatility is measured by the VDAX, and lagged sentiment is proxied by the SAFE index. FF6 controls include MKT, SMB, HML, MOM, RMW, and CMA. Newey–West t-statistics with one lag are reported in parentheses.

Source: Own Analysis

Table 4-5: Market States and the Dynamics of Salience Effect

To complement the discrete analysis, Table 4-5 reports results from time-series regressions of long-short salience portfolio returns on lagged market state variables. For equal-weighted portfolios, lagged volatility (VDAX) exhibits a negative but statistically insignificant coefficient across both specifications, confirming the directional but fragile pattern noted above. Lagged sentiment (SAFE index) has no meaningful impact on returns, with coefficients close to zero. For value-weighted portfolios, lagged sentiment shows a marginally more pronounced negative coefficient (−0.779, $t = -1.85$ without controls), suggesting that higher sentiment is associated with weaker salience effects, but this relationship loses significance once standard risk factors are included.

Two limitations of this analysis deserve explicit acknowledgment. First, the SAFE index is a manager-based sentiment measure, constructed from surveys of institutional investors, and is therefore not directly comparable to the retail-investor-oriented Baker-Wurgler (2006) index used in both Cosemans & Frehen (2021) and Cakici & Zaremba (2022). This difference in proxy construction limits the comparability of the sentiment results across studies. Second, the VDAX series is only available from 2001 onward, and the SAFE Manager Sentiment Index from 2003 onward, which constrains the time-series power of the tests relative to the full sample period used in the cross-sectional analysis.

Taken together, the results provide limited evidence of state dependence in the salience effect. Although the effect tends to be directionally stronger during periods of high volatility and low sentiment, these differences are not statistically robust. The salience effect persists across all tested market environments, suggesting that it reflects a relatively stable behavioral phenomenon rather than a conditionally driven anomaly.

4.4. Main empirical findings

This section integrates the evidence obtained from portfolio sorts, cross-sectional regressions, and market state specifications.

First, the portfolio analysis provides clear evidence of a salience effect in the German equity market. Stocks with high salience systematically underperform those with low salience, yielding negative and economically meaningful returns for long-short salience strategies. The effect is particularly pronounced in equal-weighted portfolios, indicating that it is primarily driven by smaller firms, where limits to arbitrage are likely to be more severe. In contrast, the effect is weaker and statistically insignificant in value-weighted portfolios, suggesting that it attenuates among larger, more liquid stocks.

Second, the cross-sectional regression results confirm the predictive power of salience for future returns. The negative relation between salience and subsequent performance remains robust after controlling for standard firm characteristics, including the Fama-French six-factor model, and is not absorbed by short-term reversal. This indicates that the salience effect cannot be explained by conventional risk-based or microstructure-based explanations and instead points toward a behavioral origin.

Third, the market state analysis reveals that the salience effect in Germany is broadly stable across different economic environments. While directionally stronger during high-volatility and low-sentiment periods, these differences are not statistically significant.

Taken together, the findings suggest that the salience effect in the German market is robust but not strongly state-dependent. It persists across different portfolio constructions and model specifications yet does not appear to be meaningfully driven by fluctuations in aggregate market conditions. Section 4.5 examines whether a behaviorally motivated recalibration of the salience measure alters these conclusions.

4.5. Germany specific Model

This section extends the baseline analysis by introducing a country-specific calibration of the salience distortion parameter. The motivation, empirical results, and comparison with the standard specification are presented in the following subsections.

4.5.1. Alternative Salience-Distortion Parameter

The construction of the salience measure in Section 3.2. relies on a set of parameters that govern how strongly investors overweight salient return realizations relative to less prominent outcomes. In particular, the parameter $\delta \in (0,1)$ plays a central role, as it determines the extent to which highly salient states receive disproportionate decision weight. Lower values of δ imply a stronger distortion of objective probabilities, such that the most salient return realizations exert a larger influence on the perceived payoff distribution. In contrast, values of δ closer to one imply weaker distortion, with subjective probabilities approaching their objective counterparts. In the baseline specification, this study follows the existing literature and adopts the standard calibration of $\delta = 0.7$ (Cakici & Zaremba, 2022).

While this benchmark facilitates comparability with prior studies, it implicitly assumes that the strength of attentional distortion is invariant across markets and investor populations. This assumption may be restrictive in the present setting, because the analysis focuses on the German equity market. Investor behavior can differ across countries due to cultural traits, institutional structures, and underlying economic preferences. Therefore, this section recalibrates the salience parameter to reflect behavioral characteristics that are more specific to Germany.

The first motivation comes from Hofstede's cultural dimensions framework, which is based on large-scale survey evidence originally collected among IBM employees. One relevant dimension is uncertainty avoidance, which captures the extent to which individuals in a society feel uncomfortable with uncertainty and unexpected outcomes. Germany is typically characterized by higher uncertainty avoidance than the United States (*The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.). This suggests that German investors may react more strongly to uncertain or extreme return realizations, especially when these outcomes stand out relative to a benchmark. In the context of salience theory, such behavior is consistent with a stronger overweighting of salient states.

This interpretation is further supported by country-level evidence from the Global Preference Survey (Falk et al., 2018). The GPS provides standardized measures of economic preferences across countries, including patience and willingness to take risks. Germany has a risk-taking score of -0.04449, whereas the United States has a score of 0.11659. This indicates that German individuals are, on average, less willing to take risks than individuals in the United States. Germany also has a patience score of 0.62440, compared with 0.81126 for the United States (Falk et al., 2018). These differences suggest that the German investor environment is not identical to the US-based setting that often motivates standard behavioral calibrations.

Taken together, Hofstede's uncertainty avoidance dimension and the GPS preference measures point to systematic behavioral differences between Germany and the United States. In particular, the German setting is characterized by lower risk-taking and greater sensitivity to uncertainty. From the perspective of salience theory, this can imply a stronger reaction to return realizations that are extreme, unusual, or otherwise attention-grabbing. Since the strength of this distortion is governed by δ, a stronger salience distortion corresponds to a lower value of δ.

Based on this reasoning, the following hypothesis is formulated: the strength of salience distortions in the German equity market may exceed that implied by the standard calibration, such that a lower value of δ provides a more appropriate empirical representation of investor behavior.

To examine this hypothesis, the salience measure is recalculated using $\delta = 0.5$, instead of the baseline value of $\delta = 0.7$. Importantly, this exercise is not a robustness check. Rather, it represents a behaviorally motivated country-specific calibration of the model. The empirical framework remains unchanged, and only the parameter governing the strength of salience distortions is adjusted. This allows for a direct comparison between the standard specification and a German-specific calibration.

4.5.2. Portfolio sorts

To assess the economic implications of the Germany-specific salience calibration, stocks are sorted into quintile portfolios based on the lagged salience measure constructed with a distortion parameter of $\delta = 0.5$. As in the baseline specification, quintile 1 contains stocks with the highest salience, while quintile 5 includes those with the lowest salience. The analysis focuses on the return differential between these portfolios, captured by a long-short strategy that buys high-salience stocks and shorts low-salience stocks. The equal-weighted long-short portfolio, defined as the return differential between high-salience and low-salience stocks (Q1-Q5), yields an average return of -1.07% per month. This return is statistically significant, with a Newey-West adjusted t-statistic of -5.37 (see Appendix, Table 7-17). The negative sign indicates that high-salience stocks underperform low-salience stocks, consistent with the predictions of salience theory. This pattern suggests that investors overreact to salient return realizations, leading to temporary mispricing that subsequently reverses.

Risk-Adjusted Returns (Equally-Weighted): German-Specific Calibration

	Coefficient	Std. Error	t-statistic	p-value
Alpha (α)	-0.0098	0.0023	-4.31	0.000
MKT	0.0698	0.0448	1.54	0.125
SMB	-0.0502	0.1092	-0.56	0.577
HML	-0.4002	0.1452	-2.76	0.006
MOM	-0.0472	0.0656	-0.71	0.467
RMW	-0.2130	0.1134	-1.88	0.061
CMA	0.0265	0.1006	0.26	0.792

Notes: This table reports risk-adjusted returns of the equal-weighted long–short portfolio using the German-specific salience calibration. Alpha is estimated from a time-series regression on the Fama–French five factors and momentum. Newey–West standard errors with one lag are used.

Source: Own Analysis

Table 4-6: Risk-Adjusted Returns (Equally-Weighted): German-Specific Calibration

Adjusting for common risk factors does not materially alter this finding. As it can be seen in Table 4-6, in the six-factor model, the intercept remains economically large and statistically significant at −0.98% per month ($t = -4.31$). This indicates that the return differential cannot be explained by standard systematic risk exposures and instead reflects a distinct behavioral pricing effect.

For value-weighted portfolios, the long-short return (Q1-Q5) amounts to -0.50% per month and is marginally statistically significant, with a Newey-West adjusted t-statistic of −1.97 (see Appendix, Table 7-18). While the negative sign again indicates that high-salience stocks underperform, the weaker statistical significance suggests that the effect is less pronounced among larger firms.

Risk-Adjusted Returns (Value-Weighted): German Calibration

	Coefficient	Std. Error	t-statistic	p-value
Alpha (α)	-0.00327	0.00277	-1.18	0.239
MKT	0.0657	0.0740	0.88	0.377
SMB	-0.0324	0.1553	-0.21	0.835
HML	-0.4553	0.1432	-3.18	0.002
MOM	-0.1297	0.0976	-1.33	0.184
RMW	-0.2361	0.1398	-1.69	0.092
CMA	0.2733	0.1532	1.79	0.074

Notes: This table reports risk-adjusted returns of the value-weighted long–short portfolio using the German-specific salience calibration. Alpha is estimated from a time-series regression on the Fama–French five factors and the momentum factor. Newey–West standard errors with one lag are used.

Source: Own Analysis

Table 4-7: Risk-Adjusted Returns (Value-Weighted): German-Specific Calibration

As shown in Table 4-7, after controlling for risk factors, the estimated alpha declines in magnitude and becomes statistically insignificant (α = -0.0033, t = -1.18). This attenuation implies that part of the return differential in value-weighted portfolios may be captured by factor exposures. Overall, the results point to a salience effect that is primarily concentrated in smaller, less efficiently priced stocks, where behavioral biases are more likely to persist.

The comparison between the standard calibration (δ = 0.7) and the Germany-specific calibration (δ = 0.5) reveals a nuanced pattern. In the equal-weighted specification, the magnitude and statistical significance of the long-short return remain strong under the Germany-specific calibration, indicating that a stronger distortion parameter continues to generate economically meaningful return differentials. This is consistent with the theoretical interpretation of δ: a lower value implies that investors place greater weight on salient outcomes, thereby increasing the potential for mispricing and subsequent return reversal (Bordalo et al., 2013; Cosemans & Frehen, 2021).

In contrast, the value-weighted results show a more moderate effect. While the raw long-short return is economically meaningful and marginally significant, its statistical significance disappears after controlling for risk factors. This suggests that the salience effect under δ = 0.5 remains primarily concentrated in smaller firms, where limits to arbitrage and lower informational efficiency allow behavioral biases to have a stronger impact on prices. This interpretation is verified by the portfolio characteristics, which reveal a pronounced size gradient across salience-sorted portfolios (see Appendix, Table 7-19). Firms in the highest salience quintile exhibit substantially lower average market capitalization than those in the lowest quintile, particularly in the equally weighted specification. Although value-weighting increases the average firm size across portfolios, reflecting the greater influence of large-cap stocks, the relative differences persist. This evidence confirms that high-salience portfolios are systematically tilted towards smaller firms, providing a structural explanation for why the salience effect remains economically meaningful in equal-weighted portfolios but weakens in value-weighted specifications. This interpretation is further corroborated by a direct size-split analysis (see Appendix, Table 7-20), which confirms that the salience effect is exclusively present among small-cap stocks and absent among large-cap firms under both calibrations.

A comparison between equally weighted and value-weighted specifications under the German calibration reveals a consistent pattern (see Appendix, Table 7-21). While the equally weighted long-short portfolio exhibits economically large and statistically significant returns, the magnitude is notably reduced, and statistical significance weakens under value weighting. The same pattern holds for risk-adjusted performance, with the alpha remaining significant in the equally weighted case but becoming insignificant once value weighting is applied. This attenuation indicates that the salience effect under the German

calibration is primarily concentrated among smaller firms and does not translate into robust abnormal returns in value-weighted portfolios.
Overall, the findings provide support for the hypothesis that the strength of salience distortions varies across investor populations and market environments. The Germany-specific calibration, motivated by cultural and preference-based differences, confirms the presence of a salience effect, particularly in segments of the market where behavioral biases are less likely to be arbitraged away.

4.5.3. Fama-MacBeth Regressions

To further examine the cross-sectional pricing implications of the Germany-specific salience measure, Fama-MacBeth (1973) regressions are estimated. In each month, next-period stock returns are regressed on the contemporaneous salience measure and a set of control variables, and the resulting slope coefficients are averaged over time. This framework allows for a direct assessment of whether salience predicts the cross-section of expected returns.

Fama–MacBeth Regressions of Future Returns: German Calibration

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: r_{t+1}					
ST_germany	-0.0868***	-0.0912***	-0.0872***	-0.0878***	-0.0907***	-0.0976***
	(0.0163)	(0.0162)	(0.0159)	(0.0155)	(0.0151)	(0.0149)
Size		-0.0010***	-0.0003	-0.0013***	-0.0013***	-0.0013***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
BM			8.7655***	8.6593***	8.0321***	8.3173***
			(0.8415)	(0.7927)	(0.7930)	(0.7818)
ROA				0.0010***	0.0010***	0.0010***
				(0.0001)	(0.0001)	(0.0001)
Asset Growth					-0.5128	-0.7257
					(0.5704)	(0.6087)
REV						0.0002
						(0.0050)
Constant	0.0093***	0.0144***	0.0040	0.0077***	-0.0096	-0.0122
	(0.0028)	(0.0031)	(0.0030)	(0.0028)	(0.0124)	(0.0125)
Observations	220,415	220,415	220,415	220,415	220,415	216,037
Time periods	420	420	420	420	420	419
Avg. R^2	0.0095	0.0195	0.0270	0.0419	0.0457	0.0532

Notes: This table reports Fama–MacBeth (1973) cross-sectional regressions of future stock returns (r_{t+1}) using the German-specific salience calibration ($\delta = 0.5$). Newey–West corrected standard errors with one lag are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own Analysis

Table 4-8: Fama-MacBeth Regressions of Future Returns: German-Specific Calibration

The baseline regression shown in Table 4-8 reveals a strong and statistically significant relation between salience and future returns. The estimated coefficient on ST^{GER} is −0.0868 (significant at the 1% level), indicating that higher salience is associated with significantly lower subsequent returns. This finding is consistent with the portfolio sort results and supports the interpretation that investors overreact to salient return realizations, leading to predictable return reversals.
The inclusion of firm size as a control variable does not attenuate the salience effect. The coefficient on salience remains negative and becomes even slightly stronger in magnitude (−0.0912, significant at the 1% level), while size itself enters with a significantly negative coefficient, consistent with the well-documented size effect.

Adding book-to-market further confirms the robustness of the salience effect. The coefficient on salience remains highly significant (−0.0872, significant at the 1% level), while BM exhibits a strong positive relation with returns, in line with the value premium. The size effect becomes statistically insignificant in this specification, suggesting overlap between size and value characteristics.
The results remain stable when additional controls are introduced. Including profitability (ROA) yields a salience coefficient of −0.0878 (significant at the 1% level), while ROA itself is strongly positively related to future returns. In specification (5), which also includes asset growth, the coefficient on salience remains economically large and statistically significant at −0.0906 (significant at the 1% level). Specification (6) additionally controls for short-term reversal (REV). The salience coefficient remains negative and highly significant at −0.0976, while REV itself is statistically insignificant. This confirms that the salience effect under the German-specific calibration is not driven by return reversal dynamics, consistent with the baseline findings in Section 4.2.
Importantly, the inclusion of asset growth does not materially affect the salience coefficient, and the variable itself is statistically insignificant. This suggests that the predictive power of salience is not driven by investment-related effects captured by asset growth.
Across all specifications, the coefficient on the Germany-specific salience measure is consistently negative and statistically significant at the 1% level. The magnitude of the effect is economically meaningful and remarkably stable, indicating that salience captures a robust source of cross-sectional variation in expected returns that is not subsumed by standard firm characteristics.
These findings provide strong evidence that the salience effect persists in the German equity market when the distortion parameter is calibrated to reflect country-specific behavioral characteristics. The results are consistent with the notion that investors overweight salient return realizations, leading to temporary mispricing that subsequently reverses.

The comparison of the Fama-MacBeth regression results across the two parameterizations reveals a clear and systematic pattern: the magnitude of the salience effect is substantially reduced under the Germany-specific calibration ($\delta = 0.5$), while its statistical significance remains strong. In the baseline specification without control variables, the coefficient on salience declines from −0.1595 under $\delta = 0.7$ to −0.0868 under $\delta = 0.5$. This reduction in magnitude persists across all model specifications. In the most comprehensive regression, the coefficient decreases from −0.1823 to −0.0976, indicating that the economic strength of the salience effect is nearly halved when the distortion parameter is recalibrated.

Despite this attenuation, the salience coefficient remains highly statistically significant in all specifications under both calibrations. Moreover, the stability of the coefficient across different sets of control variables is preserved, suggesting that the predictive power of salience is robust to the inclusion of standard firm characteristics such as size, book-to-market, profitability, and asset growth, and short-term reversal. At first glance, the reduction in magnitude may appear counterintuitive, given the hypothesis that German investors exhibit stronger salience distortions. However, this pattern can be rationalized by considering how the distortion parameter affects the construction of the salience measure. A lower value of δ concentrates the salience measure on the most extreme return realizations, which reduces the overall cross-sectional dispersion of ST and thereby mechanically produces a smaller estimated regression coefficient. As a result, the cross-sectional dispersion of the salience measure may decrease for a large portion of the sample, leading to a smaller estimated slope coefficient in the regression framework.

4.5.4. Market States

This section examines whether the salience effect under the Germany-specific calibration varies across different market environments. As in Section 4.3, the analysis employs both a discrete median-split framework and continuous time-series regressions, using the VDAX and the SAFE Manager Sentiment Index as proxies for market conditions.

The Salience Effect in Different Market States: German-Specific Calibration

	Equal-weighted portfolios		Value-weighted portfolios	
	$\bar{R}$	α_6	$\bar{R}$	α_6
Panel A: Volatile versus stable markets				
High market volatility	-1.80		0.01	
Low market volatility	-0.94		-0.76	
High − Low	-0.85	-0.64	0.78	0.75
		(-1.21)		(1.02)
Panel B: High versus low sentiment markets				
High sentiment	-0.80		-0.55	
Low sentiment	-1.60		-0.19	
High − Low	0.79	0.76	-0.36	-0.30
		(1.63)		(-0.47)

Notes: This table reports monthly returns of long–short salience portfolios across different market states using the German-specific salience calibration with $\delta = 0.5$. Panel A splits months into high- and low-volatility periods based on the median of lagged market volatility. Panel B splits months into high- and low-sentiment periods based on the median of lagged sentiment. $\bar{R}$ denotes the average monthly return. α_6 denotes the FF6-adjusted High–Low difference estimated from time-series regressions including MKT, SMB, HML, MOM, RMW, and CMA as control variables. Newey–West adjusted t-statistics with one lag are reported in parentheses.

Source: Own Analysis

Table 4-9: The Salience Effect in Different Market States: German-Specific Calibration

The results presented in Table 4-9 provide evidence on the state dependence of the salience effect under the Germany-specific calibration (δ = 0.5). Consistent with the baseline specification, the equal-weighted long-short portfolio yields negative returns across both volatility and sentiment regimes, although the High−Low spread in Panel B turns positive, indicating that the effect is somewhat weaker during high-sentiment periods, indicating that the salience effect persists independently of prevailing market conditions. In economic terms, the effect is more pronounced during periods of high market volatility (-1.80%) compared to low-volatility periods (-0.94%), and similarly stronger during low-sentiment regimes (-1.60%) than during high-sentiment periods (-0.80%). This pattern is consistent with the notion that attention-driven distortions may be amplified in environments characterized by uncertainty and pessimism. However, the differences between market states are not statistically significant, as reflected in the insignificant High-Low return spreads and the corresponding FF6-adjusted alphas.

For value-weighted portfolios, the results are weaker and less consistent. Return differentials across market states are economically small and statistically insignificant, and in some cases even change sign. This confirms that the salience effect under the Germany-specific calibration remains concentrated in smaller firms and does not translate into robust return predictability among larger, more liquid stocks. Overall, the findings mirror those of the baseline analysis and suggest that, while the economic magnitude of the salience effect varies somewhat across market environments, there is no strong statistical evidence of state dependence. Instead, the results support the interpretation that salience-driven mispricing represents a relatively stable behavioral phenomenon in the German equity market, rather than a conditionally driven effect that is confined to specific market regimes.

Market States and the Dynamics of the Salience Effect: German-Specific Calibration

	Equal-weighted portfolios		Value-weighted portfolios	
	No controls	FF6 controls	No controls	FF6 controls
Lagged volatility (VDAX)	-0.061	-0.054	-0.037	-0.034
	(-1.29)	(-1.13)	(-0.41)	(-0.38)
Lagged sentiment (SAFE)	0.124	0.124	-0.763	-0.730
	(0.42)	(0.43)	(-1.44)	(-1.38)
Controls (FF6)	No	Yes	No	Yes
Observations	214	214	214	214

Notes: This table reports time-series regressions of long–short salience portfolio returns based on the German-specific calibration ($\delta = 0.5$) on lagged market state variables. Lagged volatility is measured by the VDAX, and lagged sentiment is measured by the SAFE Manager Sentiment Index. FF6 controls include MKT, SMB, HML, MOM, RMW, and CMA. Newey–West adjusted t-statistics with one lag are reported in parentheses.

Source: Own Analysis

Table 4-10: Market States and the Dynamics of the Salience Effect: German-Specific Calibration

The results in Table 4-10 provide further evidence on the dynamic relation between the salience effect and market conditions under the Germany-specific calibration. In line with the baseline findings, the coefficients on lagged market volatility are negative across all specifications, suggesting that the salience effect tends to be stronger in periods of elevated uncertainty. However, the estimated effects are economically small and statistically insignificant, indicating that volatility does not systematically drive the cross-sectional return spread associated with salience.

Similarly, the relationship between lagged sentiment and the salience effect remains weak. While the equal-weighted specification yields a positive coefficient, implying a slightly stronger salience effect in high-sentiment environments, the estimates are not statistically significant. For value-weighted portfolios, the coefficients are negative, but again imprecisely estimated. Importantly, the inclusion of Fama-French six-factor controls leave the results largely unchanged, confirming that the lack of statistical significance is not driven by omitted risk factors.

Overall, the continuous regression evidence confirms the results from the median-split analysis: although there are mild indications that the salience effect varies across market environments, there is no robust statistical support for strong state dependence. Instead, the findings suggest that the salience-driven return patterns under the Germany-specific calibration are relatively stable over time and not systematically amplified or attenuated by fluctuations in market volatility or investor sentiment.

4.5.5. Comparison

The comparison between the standard calibration ($\delta = 0.7$) and the Germany-specific calibration ($\delta = 0.5$) reveals a nuanced pattern regarding the role of salience distortions in asset pricing. While the behavioral motivation for a lower distortion parameter suggests a stronger overweighting of salient outcomes, the empirical results indicate that the effect of this recalibration is not uniform across specifications.

In the portfolio-sorting framework, the Germany-specific calibration preserves the key qualitative findings of the baseline model. In equal-weighted portfolios, the long-short return remains economically large and statistically significant, indicating that salience continues to generate substantial cross-sectional variation in expected returns. The magnitude of the return differential is comparable to that obtained under the standard calibration, with minor differences reflecting the distributional compression induced by the lower distortion parameter.

However, this pattern does not extend uniformly to value-weighted portfolios. While the raw long-short return under δ = 0.5 is economically meaningful and marginally significant, its statistical significance disappears after controlling for standard risk factors. This pattern closely mirrors the baseline results and reinforces the conclusion that salience-driven mispricing is primarily concentrated in smaller and less liquid stocks. In larger firms, where arbitrage is more effective, the effect remains weak and largely absorbed by common risk factors.

The regression-based evidence provides further insight into the impact of the recalibration. While the salience coefficient remains statistically significant at the 1% level across specifications, its magnitude is notably smaller under δ = 0.5 compared to δ = 0.7. This apparent attenuation reflects the non-linear nature of the salience transformation: a lower distortion parameter increases the relative weight of extreme outcomes but compresses variation among moderately salient observations. As a result, the cross-sectional dispersion of the salience measure is altered, leading to smaller estimated coefficients despite the persistence of strong statistical significance.

Taken together, the results suggest that the Germany-specific calibration does not uniformly strengthen the measured salience effect but rather modifies its empirical representation. The salience effect remains economically meaningful and statistically significant, particularly in the small-cap segment, but its magnitude and distribution across firms depend sensitively on the parameterization of the salience function. These findings highlight that behavioral distortions linked to salience are present in the German equity market, yet their empirical manifestation is shaped both by market structure and by the modelling choices used to capture investor attention.

5. Discussion

This section interprets the empirical findings of the preceding analysis, situates them within the broader theoretical framework, and draws out their implications for behavioral asset pricing. Section 5.1 discusses the interpretation of the main findings in light of the salience mechanism and the limits-to-arbitrage framework. Section 5.2 compares the results with international evidence. Section 5.3 addresses the behavioral implications, and Section 5.4 discusses the practical implications and limitations of the study.

5.1. Interpretation of Main Findings

The results documented above are consistent with the theoretical mechanism introduced in Section 2.1: investors allocate disproportionate attention to outcomes that stand out relative to a reference point, generating excess demand and temporary overpricing in stocks with salient upsides (Bordalo et al., 2013). When salient outcomes coincide with high returns, investors overweight the upside potential of the asset. As prices subsequently adjust toward fundamental value, this overvaluation is corrected, resulting in lower subsequent returns. The negative relation between salience and future returns observed in this study is therefore consistent with an attention-driven mispricing mechanism rather than a compensation for systematic risk. The construction of the salience measure as the covariance between salience weights and returns directly reflects this mechanism, as it captures whether investor attention is concentrated on positive or negative payoff states (Cosemans & Frehen, 2021).

An important implication of the results is that the salience effect is not uniformly distributed across the market. The pronounced difference between equally-weighted and value-weighted portfolios indicates that the effect is primarily concentrated among smaller firms. This is consistent with the limits-to-arbitrage framework of Shleifer & Vishny (1997): smaller firms typically exhibit lower liquidity, higher transaction costs, and reduced analyst coverage, all of which hinder the correction of mispricing and allow attention-driven distortions to persist. In contrast, the attenuation of the effect in value-weighted portfolios reflects the greater effectiveness of arbitrage mechanisms among larger, more liquid stocks.

The regression results reinforce this interpretation and add an important qualification. The salience coefficient is stable across all model specifications and, notably, does not attenuate when short-term reversal (REV) is added as a control, it marginally strengthens. This is worth emphasizing because the ST measure is mechanically constructed from recent daily return deviations, which creates a natural overlap with past one-month returns. Since ST and REV share common inputs, part of what looks like a salience effect could in principle reflect non-behavioral phenomena: the short-term reversal anomaly is itself frequently attributed to market microstructure forces such as bid-ask bounce, price pressure from liquidity provision, rather than to cognitive biases (Cakici & Zaremba, 2022). If salience and reversal were capturing the same underlying dynamic, controlling for REV would sharply reduce the salience coefficient. The German evidence shows the opposite: the salience coefficient is not a repackaging of reversal dynamics but instead identifies a behaviorally distinct source of return predictability, one that survives after the microstructure-related component is absorbed by the REV control.

The Germany-specific calibration introduces a further important nuance. Motivated by cross-country evidence on lower risk tolerance and stronger uncertainty avoidance among German investors (Falk et al., 2018; *The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.), the distortion parameter was recalibrated to $\delta = 0.5$ to provide a more behaviorally accurate representation of this investor population. The empirical results confirm the presence of the salience effect under this alternative calibration, but the magnitude of the regression coefficients is smaller rather than larger compared to the standard parameterization. This reflects the non-linear structure of the salience transformation: a lower δ concentrates the measure on the most extreme return realizations while compressing variation among moderately salient observations, reducing cross-sectional dispersion in ST and thereby mechanically producing smaller estimated regression coefficients.

Finally, the market state analysis suggests that the salience effect in the German market is relatively stable over time rather than strongly state-dependent. Although the effect is economically somewhat more pronounced during periods of high volatility and low sentiment, the differences across market regimes are not statistically significant. The salience effect therefore appears to reflect a persistent behavioral mechanism operating continuously in this market, rather than a phenomenon that emerges only under particular aggregate conditions.

5.2. Comparison with International Evidence

Relative to the existing literature, the findings of this thesis both confirm and extend the empirical relevance of salience theory in asset pricing. While prior evidence, which is primarily based on the US market, documents a negative relationship between salience and future returns (Cosemans & Frehen, 2021), the results for Germany suggest that its empirical manifestation is shaped by market structure rather than sentiment cycles.

The German results are consistent with the international evidence documenting that the salience anomaly is concentrated among the smallest firms and attenuates substantially once larger stocks receive proportionally greater weight (Cakici & Zaremba, 2022). The equally-weighted results for Germany confirm the presence of salience-driven mispricing, while the attenuation in value-weighted portfolios aligns with this global pattern. This pattern is consistent with the broader international evidence, in which limits to arbitrage systematically determine where the salience effect survives across markets (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021).

A further point of distinction concerns the relationship between salience and short-term reversal. Whereas Cakici & Zaremba (2022) find internationally that a substantial portion of salience strategy returns overlaps with the short-term reversal effect, raising concerns that the anomaly may partly reflect market microstructure forces rather than genuine behavioral mispricing, the German evidence does not support this interpretation. Controlling for the lagged one-month return does not attenuate the salience coefficient but marginally strengthens it, suggesting that salience captures a behaviorally distinct source of return predictability in this market that is not a repackaging of reversal dynamics.

Another important distinction relates to the role of market conditions. Whereas previous studies find that salience effects are amplified in high-sentiment environments (Cosemans & Frehen, 2021) or following severe market downturns (Cakici & Zaremba, 2022), the German evidence does not support a statistically robust state dependence under either proxy. The salience effect persists across all tested market regimes, suggesting that attention-driven mispricing in this market operates as a relatively stable behavioral phenomenon rather than one that is conditionally amplified by aggregate fluctuations in sentiment or volatility.

Finally, the introduction of a Germany-specific calibration highlights an additional dimension along which the results deviate from the standard literature. While most studies rely on a common parameterization of the salience model, the findings here suggest that behavioral parameters are not directly transferable across markets. The sensitivity of the empirical results to the distortion parameter underscores that cross-country differences in risk preferences can affect not only investor behavior but also how such behavior is captured empirically.

Taken together, these results suggest that salience theory has external validity beyond the US context, but that its quantitative importance and empirical characteristics depend on where in the market structure limits to arbitrage are most binding and on how the salience measure is parameterized. The German case therefore contributes to the literature by illustrating that behavioral asset pricing effects are real but structurally conditioned, present where mispricing can persist and absent where arbitrage is effective.

5.3. Behavioral Implications of Salience in Asset Pricing

The findings of this thesis provide several insights into how investor attention and perception influence asset prices in practice. At a general level, the results support the view that investors do not process information in a fully rational and symmetric manner, but instead overweight outcomes that are more salient relative to a reference point. The investors' attention is endogenously directed toward states of the world that stand out, leading to distorted probability weighting and biased expectations (Bordalo et al., 2013).

A central implication of the empirical evidence is that salience operates as a systematic source of mispricing rather than as a proxy for risk. The persistence of the salience effect after controlling for standard asset pricing factors suggests that the observed return differences are unlikely to reflect compensation for exposure to conventional risk dimensions. Instead, the results are more consistent with a mechanism in which investors temporarily overreact to salient return realizations, causing prices to deviate from fundamental values. The subsequent correction of these deviations then generates predictable return patterns. This interpretation places salience within the broader class of attention-based behavioral biases that generate predictable cross-sectional return patterns (Bordalo et al., 2013).

At the same time, the concentration of the effect among smaller firms provides important insight into the conditions under which behavioral biases translate into observable pricing effects. The results suggest that attention-driven distortions are not sufficient on their own to generate persistent mispricing. Rather, they must interact with limits to arbitrage. In segments of the market where trading frictions, information asymmetries, and short-selling constraints are more pronounced, mispricing is more likely to persist and become empirically detectable (Cosemans & Frehen, 2021; Shleifer & Vishny, 1997). This highlights the importance of integrating behavioral models with market frictions when analyzing real-world asset pricing phenomena.

Another implication concerns the stability of investor behavior across different market environments. The absence of strong state dependence in the empirical results suggests that salience-driven attention distortions may represent a relatively stable feature of investor decision-making, rather than a phenomenon that emerges only in periods of extreme sentiment or uncertainty. This suggests that the absence of robust state dependence is itself informative: salience-driven mispricing does not require specific market conditions to emerge, but appears to be a persistent feature of how investors process return information.

The Germany-specific calibration also carries a broader behavioral implication: the strength of attentional distortions is not uniform across investor populations. Evidence on risk preferences and uncertainty avoidance suggests that the cognitive intensity of salience distortions may vary systematically across countries (Falk et al., 2018; *The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.). This means that behavioral parameters derived from one market context should not be applied to other markets without considering the characteristics of the local investor population.

Finally, the findings contribute to the broader debate on the role of investor attention in financial markets. While a growing literature emphasizes the importance of attention constraints and salience in shaping asset prices, empirical evidence outside the US remains limited. By showing that salience effects are present in Germany but do not vary significantly across market states, attention-based models capture a general behavioral tendency, but that their empirical manifestation depends on where in the market structure limits to arbitrage allow mispricing to persist. This reinforces the view that behavioral finance should not be seen as a collection of universal anomalies, but as a framework in which psychological biases interact with market structure to determine observed outcomes.

5.4. Implications and Limitations

The findings of this study have important implications for both investment practice and the understanding of market efficiency. At the same time, several limitations should be acknowledged, which are relevant for interpreting the results and for guiding future research.

A first limitation relates to the measurement of salience. The empirical proxy is constructed from daily return deviations relative to a market benchmark and aggregated to the monthly level. While this approach closely follows the existing literature, it inevitably simplifies the underlying behavioral concept. Salience in reality may arise not only from return realizations, but also from news, narratives, or other attention-grabbing events that are not fully captured by price-based measures. As a result, the constructed salience variable should be interpreted as an approximation of investor attention rather than a direct observation of it (Bordalo et al., 2013; Cosemans & Frehen, 2021).

A second consideration concerns the potential overlap between salience and short-term reversal. Although controlling for the lagged one-month return does not attenuate the salience coefficient in the German sample, more refined tests such as excluding the last day's return from the estimation period, as applied by Cakici & Zaremba (2022), would further sharpen this distinction and remain an avenue for future robustness analysis.

A third limitation relates to the implementation of the trading strategies used to assess economic significance. The abnormal returns documented in the portfolio analysis are based on gross returns and do not account for transaction costs, bid-ask spreads, or short-selling constraints. This is particularly relevant given that the salience effect is concentrated in smaller and less liquid stocks, where trading frictions are likely to be substantial. The literature on limits to arbitrage highlights that such frictions can significantly reduce the profitability of anomaly-based strategies (Barberis et al., 2006). As a result, the economic feasibility of exploiting the salience premium in practice may be more limited than suggested by the reported returns.

A fourth limitation concerns the analysis of market states. While the study employs two complementary proxies for market conditions, the SAFE Manager Sentiment Index and the VDAX, the available time series for these variables is relatively limited, especially for sentiment. This reduces the statistical power of the tests and may partly explain the lack of strong evidence for state dependence. Previous studies have shown that detecting time variation in behavioral effects requires sufficiently long samples and precise proxies for investor sentiment (Cosemans & Frehen, 2021). Moreover, the SAFE Manager Sentiment Index captures managerial expectations derived from corporate disclosures and is therefore not directly comparable to the Baker-Wurgler (2006) retail investor sentiment index employed by both Cosemans & Frehen (2021) and Cakici & Zaremba (2022). This difference in proxy construction limits the comparability of the sentiment results across studies and may partly explain why the sentiment channel appears weaker in the present analysis than in the US evidence.

A fifth limitation concerns the absence of out-of-sample validation. The empirical analysis is conducted entirely within the same sample period, such that the predictive relationships identified are not tested on independent data. This is particularly relevant for the Germany-specific calibration of $\delta = 0.5$, which is both motivated and evaluated on the same dataset, raising the possibility that the chosen parameterization is partially tailored to the specific distributional properties of the sample rather than reflecting a transferable behavioral characteristic. Whether a comparable attenuation of the salience anomaly to that documented in the US over recent decades is observable in the German market across subperiods remains an open question for future work.

Despite these limitations, the results provide several important implications. From an investment perspective, the findings suggest that attention-driven mispricing may represent a potential source of return predictability, particularly in the small-cap segment of the German equity market. However, the practical relevance of this effect depends critically on implementation costs and market frictions, which may limit its exploitability for large institutional investors.

From a broader market perspective, the results raise questions about the degree of informational efficiency in the German equity market. The presence of return predictability that is not explained by standard risk factors suggests that prices do not fully reflect all available information, at least in certain segments of the market. This is consistent with behavioral asset pricing models, which emphasize that cognitive biases and limited attention can lead to persistent deviations from fundamental values (Bordalo et al., 2013).

Finally, the findings have implications for future research in behavioral asset pricing. The sensitivity of the results to the parameterization of the salience model highlights the importance of carefully considering how behavioral mechanisms are operationalized empirically. Moreover, the differences observed between the German market and international evidence suggest that the interaction between investor behavior and market structure is a promising avenue for further investigation (Cakici & Zaremba, 2022).

6. Conclusion

This thesis set out to examine whether salience theory can explain the cross-section of stock returns in the German equity market and how this relationship varies across market conditions. Germany represents a particularly interesting setting for this question: it is one of the largest equity markets in Europe, yet it has received limited dedicated attention in the behavioral asset pricing literature, having been treated as one observation among many in broad cross-country studies. Its structural and behavioral characteristics, including survey-based evidence on lower risk tolerance and higher uncertainty avoidance among German investors relative to their US counterparts, further motivate a focused, long-sample investigation rather than a brief country-level observation embedded in international evidence.

The central result of the analysis is that stocks with higher salience measures earn significantly lower subsequent returns in the German market, consistent with the theoretical prediction of Bordalo et al. (2013) that investors overweight salient payoff realizations and thereby generate temporary overpricing. This negative relation survives adjustment for a six-factor model and, importantly, is not attenuated when short-term reversal is controlled for. This last point is worth emphasizing: international evidence documents a substantial overlap between salience strategy returns and short-term reversal, raising the concern that salience profits may partly reflect market microstructure forces rather than genuine behavioral mispricing (Cakici & Zaremba, 2022). The German evidence does not support this concern. Controlling for the lagged one-month return marginally strengthens the salience coefficient rather than reducing it, suggesting that salience captures a behaviorally distinct source of return predictability in this market.

At the same time, the value-weighted results reveal a sharp boundary: once portfolio weights reflect market capitalization, the salience effect largely disappears. This attenuation indicates that the effect is concentrated among smaller, less liquid firms where limits to arbitrage are most binding, and is largely absent in the large-cap segment where arbitrage is more effective. This size-concentration is consistent with the broader international evidence and underscores that behavioral biases and limits to arbitrage are complementary rather than competing explanations. The salience mechanism operates in the German market, but only where market structure allows mispricing to persist.

The market state analysis provides only limited evidence that the salience effect varies systematically across economic environments. Although the effect appears directionally stronger during periods of elevated volatility and low sentiment, the differences across regimes are not statistically significant under either the discrete or the continuous regression framework. This finding is noteworthy in its own right: it suggests that salience-driven mispricing in Germany reflects a persistent feature of investor behavior rather than a conditionally amplified anomaly. The salience effect does not require specific aggregate conditions to emerge, but operates continuously across different market environments.

The country-specific recalibration of the distortion parameter to $\delta = 0.5$, motivated by cross-country evidence suggesting that German investors may overweight salient outcomes more intensely than the standard calibration assumes (Falk et al., 2018; *The 6 Dimensions Model of National Culture by Geert Hofstede*, n.d.), shows that the salience effect remains economically meaningful and statistically significant under a behaviorally more appropriate parameterization for this investor population. This recalibration illustrates a broader limitation of cross-country applications of behavioral models: parameters developed in one market context are not directly portable to others, as differences in investor characteristics affect not only the strength of behavioral distortions but also how these distortions are captured empirically.

Taken together, the findings point to a conclusion that extends beyond the German context: behavioral asset pricing effects are real but conditionally present. Where arbitrage is costly and market frictions are high, attention-driven mispricing translates into observable return predictability and where arbitrage is effective, it does not. Salience should therefore not be treated as a universal anomaly, but as a mechanism whose empirical manifestation is shaped by the market structure in which it operates. Future research may usefully examine whether similar patterns hold in other European markets with comparable structural characteristics, and whether more direct measures of investor attention can sharpen the identification of salience-driven mispricing beyond what return-based proxies allow.

7. Appendices

Summary Statistics for Daily Salience

Variable	Obs	Mean	Std. Dev.	Min	Max
salience_daily	5,966,013	0.1295108	0.128846	2.33e-07	0.9262204

Notes: This table reports summary statistics for the daily salience measure across all observations in the sample. Salience is constructed as described in Section 3.2.

Source: Own Analysis

Table 7-1: Summary Statistics for Daily Salience

Summary Statistics for Salience (ST)

Variable	Obs	Mean	Std. Dev.	Min	Max
ST	5,966,013	0.006262	0.0385181	-0.3873144	0.7439007

Notes: This table reports summary statistics for the salience measure (ST) at the daily level. Salience is constructed as described in Section 3.2.

Source: Own Analysis

Table 7-2: Summary Statistics for Salience (ST)

Distributional Properties of Salience (ST)

Statistic	Value
Observations	220,415
Mean	0.0046178
Std. Dev.	0.0263755
Variance	0.0006957
Skewness	2.534557
Kurtosis	28.82326
Percentiles	
1%	-0.0530445
5%	-0.0272395
10%	-0.0181489
25%	-0.00711
50%	0.0016009
75%	0.0130082
90%	0.0290043
95%	0.0440972
99%	0.0954402

Notes: This table reports detailed distributional statistics for the salience measure (ST).

Source: Own Analysis

Table 7-3: Distributional Properties of Salience (ST)

Summary Statistics for Equally-Weighted Long–Short Portfolio

Variable	Obs	Mean	Std. Dev.	Min	Max
LS_ew	403	-0.0115206	0.0413774	-0.1892038	0.3442815

Notes: This table reports summary statistics for the long–short portfolio (LS_ew), defined as the return difference between the highest and lowest salience portfolios.

Source: Own Analysis

Table 7-4: Summary Statistics for Equally-Weighted Long-Short Portfolio

Summary Statistics for Value-Weighted Long–Short Portfolio (LS_vw)

Variable	Obs	Mean	Std. Dev.	Min	Max
LS_vw	403	-0.0034322	0.0561608	-0.2407251	0.3767382

Notes: This table reports summary statistics for the value-weighted long–short portfolio (LS_vw), constructed as the return difference between the highest and lowest salience portfolios.

Source: Own Analysis

Table 7-5: Summary Statistics for Value-Weighted Long-Short Portfolio

Average Market Capitalization by Salience Quintile

Salience Quintile	Equal-Weighted Market Cap	Value-Weighted Market Cap
Q1 (High Salience)	856.13	18,946.48
Q2	2,342.17	30,674.63
Q3	2,648.08	32,642.11
Q4	2,527.22	32,054.71
Q5 (Low Salience)	1,151.94	22,140.23

Notes: This table reports the average market capitalization across salience-sorted portfolios. Quintile 1 (Q1) contains stocks with the highest salience, while Quintile 5 (Q5) contains stocks with the lowest salience.

Source: Own Analysis

Table 7-6: Average Market Capitalization by Salience Quintile

Size-Split Portfolio Sorts: Standard Calibration ($\delta = 0.7$)

	Small Caps		Large Caps	
	$\bar{R}$	α	$\bar{R}$	α
Panel A: Returns				
Long-Short (Q1–Q5)	-0.0132^{***}	-0.0124^{***}	0.0003	0.0032
	(−6.07)	(−5.24)	(0.12)	(1.00)
Panel B: Factor Loadings				
MKT		0.0806		0.1312
SMB		−0.0386		−0.1307
HML		-0.3454^{**}		-0.6695^{**}
MOM		0.0058		-0.2892^{**}
RMW		-0.2535^{**}		−0.2587
CMA		0.0661		0.2169

Notes: This table reports returns of the long-short salience portfolio (Q1–Q5) separately for small-cap firms (bottom 10% of cumulative market capitalization) and large-cap firms (remaining 90%). $\bar{R}$ denotes the average monthly return and α the FF6-adjusted alpha. Newey–West adjusted t-statistics with one lag are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own Analysis

Table 7-7: Size-Split Portfolio Sorts: Standard Calibration

Distribution of Book-to-Market Ratio Before and After Winsorization

	Before winsorization	After winsorization
Panel A: Percentiles		
1%	0.0000376	0.0000376
5%	0.0001102	0.0001102
10%	0.0001746	0.0001746
25%	0.0003227	0.0003227
50%	0.0005556	0.0005556
75%	0.0009254	0.0009254
90%	0.0014787	0.0014787
95%	0.0020505	0.0020505
99%	0.0050051	0.0050051
Panel B: Moments		
Observations	225,446	225,446
Mean	0.0013006	0.0007593
Std. Dev.	0.0280299	0.0007480
Variance	0.0007857	0.000000560
Skewness	90.59971	3.042836
Kurtosis	9262.59	15.30848
Panel C: Extreme Values		
Smallest value	1.30e-10	0.0000376
Largest value	3.549272	0.0050051

Notes: This table reports distributional statistics for the book-to-market ratio before and after winsorization.

Source: Own Analysis

Table 7-8: Distribution of Book-to-Market Ratio Before and After Winsorization

Distribution of Return on Assets (ROA) Before and After Winsorization

	Before winsorization	After winsorization
Panel A: Percentiles		
1%	-88.38	-30.94
5%	-30.94	-30.94
10%	-13.65	-13.65
25%	0.09	0.09
50%	3.19	3.19
75%	6.70	6.70
90%	12.08	12.08
95%	17.65	17.65
99%	37.95	17.65
Panel B: Moments		
Observations	602,893	602,893
Mean	-2.014868	1.245604
Std. Dev.	310.2923	10.95684
Variance	96281.32	120.0524
Skewness	-161.5495	-1.483663
Kurtosis	28220.82	5.318684
Panel C: Extreme Values		
Smallest value	-55104.33	-30.94
Largest value	5241.96	17.65

Notes: This table reports distributional statistics for return on assets (ROA) before and after winsorization.

Source: Own Analysis

Table 7-9: Distribution of Return on Assets (ROA) Before and After Winsorization

Distribution of Asset Growth Before and After Winsorization

	Before winsorization	After winsorization
Panel A: Percentiles		
1%	-0.1487712	-0.1487712
5%	-0.0506773	-0.0506773
10%	-0.0365386	-0.0365386
25%	-0.0167355	-0.0167355
50%	0.0009256	0.0009256
75%	0.019637	0.019637
90%	0.0432448	0.0432448
95%	0.0635368	0.0635368
99%	0.3661354	0.3661354
Panel B: Moments		
Observations	644,163	644,163
Mean	5.361172	0.0060959
Std. Dev.	2837.326	0.0557528
Variance	8050419	0.0031084
Skewness	566.9731	3.259594
Kurtosis	321661.8	22.64943
Panel C: Extreme Values		
Smallest value	-1	-0.1487712
Largest value	28451.35	0.3661354

Notes: This table reports distributional statistics for asset growth before and after winsorization.

Source: Own Analysis

Table 7-10: Distribution of Asset Growth Before and After Winsorization

Distributional Properties Before and After Winsorization

	Before winsorization	After winsorization
Panel A: Book-to-Market Ratio (BM)		
Mean	0.0013006	0.0007593
Std. Dev.	0.0280299	0.0007480
Skewness	90.59971	3.042836
Kurtosis	9262.59	15.30848
Observations	225,446	225,446
Panel B: Return on Assets (ROA)		
Mean	-2.014868	1.245604
Std. Dev.	310.2923	10.95684
Skewness	-161.5495	-1.483663
Kurtosis	28220.82	5.318684
Observations	602,893	602,893
Panel C: Asset Growth		
Mean	5.361172	0.0060959
Std. Dev.	2837.326	0.0557528
Skewness	566.9731	3.259594
Kurtosis	321661.8	22.64943
Observations	644,163	644,163

Notes: This table reports key distributional statistics for firm characteristics before and after winsorization.

Source: Own Analysis

Table 7-11: Distributional Properties Before and After Winsorization

Summary Statistics of Main Variables

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Observations
Return (r_{t+1})	0.0088739	0.1487532	4.019562	82.93415	220,415
Size	5.051001	2.288583	0.4724533	2.913951	220,415
Book-to-Market	0.0007604	0.0007485	3.036786	15.26659	220,415
ROA	1.710358	10.27149	-1.577743	5.966406	220,415
Asset Growth	0.0055728	0.0539073	3.050629	22.1551	220,415

Notes: This table reports summary statistics for the main variables used in the analysis. Returns are measured as next-period stock returns (r_{t+1}). Firm characteristics include size, book-to-market ratio (BM), return on assets (ROA), and asset growth. All variables are winsorized to mitigate the influence of extreme observations.

Source: Own Analysis

Table 7-12: Summary Statistics of Main Variables

Correlation Matrix of Main Variables

	ST	r_{t+1}	Size	BM	ROA	Asset Growth
ST	1.000					
r_{t+1}	-0.0185***	1.000				
Size	-0.0543***	-0.0217***	1.000			
BM	-0.0151***	-0.0674***	-0.2239***	1.000		
ROA	-0.0378***	0.0751***	0.2288***	-0.0290***	1.000	
Asset Growth	0.0097***	0.0482***	0.0177***	0.0122***	0.0687***	1.000

Notes: This table reports pairwise Pearson correlations between the main variables. Returns (r_{t+1}) denote next-period stock returns. ST is the salience measure. *** denotes statistical significance at the 1% level.

Source: Own Analysis

Table 7-13: Correlation Matrix of Main Variables

Long–Short Portfolio Returns (Equal-Weighted)

	Mean Return	Std. Error	t-statistic	95% CI
LS_ew	-0.0115	0.00215	-5.35	[-0.0158, -0.0073]

Notes: This table reports the average return of the equal-weighted long–short portfolio (LS_ew), constructed as the difference between high- and low-salience portfolios (Q1 Q5). Newey–West standard errors with one lag are used to account for potential autocorrelation.

Source: Own Analysis

Table 7-14: Long-Short Portfolio Returns (Equally-Weighted)

Long–Short Portfolio Returns (Value-Weighted)

	Mean Return	Std. Error	t-statistic	95% CI
LS_vw	-0.00343	0.00270	-1.27	[-0.00873, 0.00187]

Notes: This table reports the average return of the value-weighted long–short portfolio (LS_vw), constructed as the difference between high- and low-salience portfolios (Q1 Q5). Newey–West standard errors with one lag are used.

Source: Own Analysis

Table 7-15: Long-Short Portfolio Returns (Value-Weighted)

Salience Portfolio Returns and Risk Adjustment

	Equal-Weighted (EW)	Value-Weighted (VW)
Panel A: Raw Returns		
Mean Return	-0.0115***	-0.00343
t-statistic	(-5.35)	(-1.27)
Panel B: Risk-Adjusted Returns (Alpha)		
Alpha (α)	-0.0101***	-0.00109
t-statistic	(-4.32)	(-0.41)
Panel C: Factor Loadings		
MKT	0.0813	0.0767
SMB	-0.0493	0.0195
HML	-0.3943**	-0.5929***
MOM	-0.0353	-0.2705**
RMW	-0.2452**	-0.1897
CMA	0.0874	0.4200***

Notes: This table reports returns of the long–short salience portfolio (Q1 Q5). Panel A shows raw average returns. Panel B reports risk-adjusted alphas from regressions on the Fama–French five factors and the momentum factor. Panel C presents factor loadings. Newey–West standard errors with one lag are used. ***, ** denote statistical significance at the 1% and 5% levels, respectively.

Source: Own Analysis

Table 7-16: Salience Portfolio Returns and Risk Adjustment

Salience Portfolio Returns (Equally-Weighted): German-Specific Calibration

	Mean Return	Std. Error	t-statistic	95% CI
LS_ew_ST_germany	-0.0107	0.00199	-5.37	[-0.0146, -0.0068]

Notes: This table reports the average return of the equal-weighted long–short portfolio based on the German-specific salience calibration. The portfolio is constructed as the difference between high- and low-salience portfolios. Newey–West standard errors with one lag are used.

Source: Own Analysis

Table 7-17: Salience Portfolio Returns (Equally-Weighted): German-Specific Calibration

Salience Portfolio Returns (Value-Weighted): German Calibration

	Mean Return	Std. Error	t-statistic	95% CI
LS_vw_ST_germany	-0.0050	0.00254	-1.97	[-0.0100, -0.0000]

Notes: This table reports the average return of the value-weighted long–short portfolio based on the German-specific salience calibration. The portfolio is constructed as the difference between high- and low-salience portfolios (Q1–Q5). Newey–West standard errors with one lag are used.

Source: Own Analysis

Table 7-18: Salience Portfolio Returns (Value-Weighted): German-Specific Calibration

Average Market Capitalization by Salience Quintile (German Calibration)

Salience Quintile	Equal-Weighted Market Cap	Value-Weighted Market Cap
Q1 (High Salience)	668.32	14,523.76
Q2	2,223.40	29,759.50
Q3	2,928.44	33,228.45
Q4	2,618.56	32,711.71
Q5 (Low Salience)	964.83	19,338.27

Notes: This table reports the average market capitalization across salience-sorted portfolios under the German-specific calibration. Quintile 1 (Q1) contains stocks with the highest salience, while Quintile 5 (Q5) contains stocks with the lowest salience. Market capitalization is reported for both equal-weighted and value-weighted portfolios.

Source: Own Analysis

Table 7-19: Average Market Capitalization by Salience Quintile (German-Specific Calibration)

Size-Split Portfolio Sorts: German-Specific Calibration ($\delta = 0.5$)

	Small Caps		Large Caps	
	$\bar{R}$	α	$\bar{R}$	α
Panel A: Returns				
Long-Short (Q1–Q5)	-0.0126^{***}	-0.0116^{***}	-0.0001	0.0028
	(-6.04)	(-5.29)	(-0.06)	(0.90)
Panel B: Factor Loadings				
MKT		0.0672		0.1313^{**}
SMB		-0.0675		-0.1870
HML		-0.3564^{***}		-0.6677^{**}
MOM		-0.0167		-0.2922^{**}
RMW		-0.1958^{*}		-0.2921
CMA		-0.0011		0.2284^{*}

Notes: This table reports returns of the long-short salience portfolio (Q1–Q5) separately for small-cap firms (bottom 10% of cumulative market capitalization) and large-cap firms (remaining 90%), using the German-specific salience calibration ($\delta = 0.5$). $\bar{R}$ denotes the average monthly return and α the FF6-adjusted alpha. Newey–West adjusted t-statistics with one lag are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own Analysis

Table 7-20: Size-Split Portfolio Sorts: German-Specific Calibration

Salience Portfolio Returns and Risk Adjustment (German Calibration)

	Equal-Weighted (EW)	Value-Weighted (VW)
Panel A: Raw Returns		
Mean Return	-0.0107***	-0.00500
t-statistic	(-5.37)	(-1.97)
Panel B: Risk-Adjusted Returns (Alpha)		
Alpha (α)	-0.0098***	-0.00327
t-statistic	(-4.31)	(-1.18)
Panel C: Factor Loadings		
MKT	0.0698	0.0657
SMB	-0.0502	-0.0324
HML	-0.4002**	-0.4553***
MOM	-0.0472	-0.1297
RMW	-0.2130*	-0.2361*
CMA	0.0265	0.2733*

Notes: This table reports returns of the long–short salience portfolio (Q1–Q5) using the German-specific calibration. Panel A shows raw average returns. Panel B reports risk-adjusted alphas from regressions on the Fama–French five factors and the momentum factor. Panel C presents factor loadings. Newey–West standard errors with one lag are used. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Own Analysis

Table 7-21: Salience Portfolio Returns and Risk Adjustment (German-Specific Calibration)

8. Bibliography and References

Allais, M. (1953). Le comportement de L'homme rationnel devant le risque: Critique des postulats et axiomes de L'école americaine. *Econometrica*, *21*, 503–546.

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18. https://doi.org/10.1016/0304-405X(81)90018-0

Barberis, N., Huang, M., & Thaler, R. H. (2006). Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing. *The American Economic Review*, *96*(4), 1069–1090. https://doi.org/10.1257/000282806779468652

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). SALIENCE THEORY OF CHOICE UNDER RISK. *The Quarterly Journal of Economics*, *127*(3), 1243–1285. https://doi.org/10.1093/qje/qjs018

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013). Salience and Asset Prices. *The American Economic Review*, *103*(3), 623–628. https://doi.org/10.1257/aer.103.3.623

Brav, A., Heaton, J. B., & Li, S. (2010). The Limits of the Limits of Arbitrage. *Review of Finance*, *14*(1), 157–187. https://doi.org/10.1093/rof/rfp018

Cakici, N., & Zaremba, A. (2022). Salience theory and the cross-section of stock returns: International and further evidence. *Journal of Financial Economics*, *146*(2), 689–725. https://doi.org/10.1016/j.jfineco.2021.10.010

Cosemans, M., & Frehen, R. (2021). Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics*, *140*(2), 460–483. https://doi.org/10.1016/j.jfineco.2020.12.012

Fadavi, S., & Hillert, A. (n.d.). *Decoding Sentiment: Methodology Behind SAFE's Manager*.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global Evidence on Economic Preferences*. *The Quarterly Journal of Economics*, *133*(4), 1645–1692. https://doi.org/10.1093/qje/qjy013

Fama, E. F. (1970). Efficient capital markets: A review of the theory and empirical work. *The Journal of finance (New York)*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *The Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2012). The impact of investor sentiment on the German stock market. *Zeitschrift Für Betriebswirtschaft*, *82*(2), 133–163. https://doi.org/10.1007/s11573-011-0536-x

Hou, K., Karolyi, G. A., & Kho, B.-C. (2011). What Factors Drive Global Stock Returns? *The Review of Financial Studies*, *24*(8), 2527–2574. https://doi.org/10.1093/rfs/hhr013

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), 65–91. https://doi.org/10.2307/2328882

Jensen, T. I., Kelly, B., & Pedersen, L. H. (2023). *Global Factor Data Documentation*.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708. https://doi.org/10.2307/1913610

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance (New York)*, *19*(3), 425-. https://doi.org/10.2307/2977928

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Shumway, T., & Warther, V. A. (1999). The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect. *The Journal of Finance (New York)*, *54*(6), 2361–2379. https://doi.org/10.1111/0022-1082.00192

The 6 dimensions model of national culture by Geert Hofstede. (n.d.). Retrieved 22 April 2026, from https://geerthofstede.com/culture-geert-hofstede-gert-jan-hofstede/6d-model-of-national-culture/

VDAX. (n.d.). Deutsche Börse Group. Retrieved 19 April 2026, from https://www.deutsche-boerse.com/dbg-en/about-us/contact/glossary/glossary-article/VDAX-249368

ZHANG, X. F. (2006). Information Uncertainty and Stock Returns. *The Journal of Finance (New York)*, *61*(1), 105–137. https://doi.org/10.1111/j.1540-6261.2006.00831.x

EXECUTIVE SUMMARY

This thesis examines the extent to which salience theory explains the cross-section of stock returns in the German equity market and investigates how different market states influence this relationship. Using a comprehensive sample of German equities spanning December 1988 to December 2023, a monthly salience measure is constructed and tested through quintile portfolio sorts, Fama-MacBeth cross-sectional regressions, a market state analysis, and a country-specific recalibration of the distortion parameter.

The central finding is that stocks with higher salience measures earn significantly lower subsequent returns, consistent with the prediction that investors overweight salient payoff realizations and thereby generate temporary overpricing. This negative relation is robust across all model specifications and survives risk adjustment under a six-factor model.

The effect is structurally concentrated among smaller, less liquid firms where limits to arbitrage are most binding, and largely absent in the large-cap segment, consistent with international evidence. The market state analysis provides only limited evidence of state dependence: although the effect is directionally stronger during high-volatility and low-sentiment periods, differences across regimes are not statistically significant. A country-specific recalibration of the distortion parameter, motivated by evidence on lower risk tolerance and higher uncertainty avoidance among German investors, yields qualitatively similar findings.

Taken together, the results suggest that salience theory provides a meaningful but structurally conditioned explanation for return predictability in the German equity market, operating as a stable behavioral mechanism rather than a conditionally amplified anomaly.

KEYWORDS: Salience Theory, Behavioral Asset Pricing, Cross-Section of Stock Returns, German Equity Market, Fama-MacBeth Regression, Portfolio Sorts, Limits to Arbitrage, Market States

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