

The Influence of Brand Value Rankings on Investment Decisions of Private Investors

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Abstract

Investment decisions of private investors are characterized by information asymmetries. Publicly visible brand value rankings can serve as decision signals by translating intangible brand strength into a comparable monetary metric. This study experimentally investigates how the visibility of such rankings affects private investors' portfolio allocation and whether this effect is moderated by investment knowledge. In an online experiment (n=244), participants assembled an investment portfolio from 20 available companies (investment opportunities). A randomized treatment group received an adapted brand value ranking beforehand, while the control group did not. The analysis examined allocation decisions along two dimensions: whether to invest (extensive margin), how much to invest (intensive margin), and portfolio breadth (number of holdings). Results show that rankings act as selection filters: participants exposed to rankings invest less frequently in unranked and low-ranked brands (extensive margin) but allocate higher amounts to top-ranked brands when they invest (intensive margin). Regarding quantity (number of holdings), the treatment group invests in significantly fewer distinct companies, particularly in the segments of lower ranks and unranked brands. While subjective investor knowledge is robustly associated with broader portfolio choice, it does not systematically neutralize the influence of the ranking. In summary, brand value rankings systematically structure investor behavior: They can influence which companies are selected, how much is allocated to each selected company, and how many different companies are held in total. The findings underscore the financial relevance of brands as behaviorally effective signals, but their external validity is limited due to the experimental design with hypothetical decisions.

Keywords: *Investment decisions, brand value, signaling theory*

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1. Introduction and problem statement

Modern Portfolio Theory (Markowitz, 1952) and the Capital Asset Pricing Model (Sharpe, 1964) form the foundation of rational investment decision-making. The Efficient Market Hypothesis postulates that capital market prices reflect all available information (Fama, 1970). However, theoretical and empirical studies highlight the limitations of this market paradigm: Grossman and Stiglitz (1980) demonstrate that markets cannot be perfectly efficient when acquiring information is costly. Similarly, Shiller (1981) shows that stock prices fluctuate far more than can be explained by changes in dividends alone. This suggests that capital market prices

do not always reflect available information completely or without distortion (Agarwal & Taffler, 2008; Grossman & Stiglitz, 1980; Shiller, 2003, Zhang 2006). These results undermine that investment decisions are fundamentally made under uncertainty.

Behavioral Finance approaches address the limitations of classical capital market models by incorporating psychological factors into the analysis of decision-making under uncertainty. While Tversky & Kahneman (1974) demonstrate that individuals rely on heuristics and simplified decision rules when making judgments under uncertainty, Prospect Theory (Kahneman & Tversky, 1979) describes systematic deviations from Expected Utility Theory in decisions involving risk. Recent findings confirm that heuristic biases, such as overconfidence or anchoring, influence investment behavior, partly by distorting risk perceptions (Jain et al., 2023). To reduce information overload in complex situations, investors utilize salient cues. Rao and Monroe (1988) show that pre-existing knowledge systematically influences the use of observable information signals in evaluation processes. Furthermore, drawing on Signalling Theory (Spence, 1973), recent studies indicate that qualitative information signals play a significant role in shaping the assessment of investment opportunities (Vazirani et al., 2023).

A brand is an intangible asset that signals quality, stability, and future earning power to investors. According to the Resource-Based View, strong brands enable competitive advantages and influence future cash flows as well as shareholder value through market-based assets (Barney, 1991; Srivastava et al., 1998). Research demonstrates that brand equity is highly relevant to capital markets, showing significant correlations with shareholder value, profitability, and financial health (Madden et al., 2006; Fehle et al., 2008; Fischer & Himme, 2017; Lo, 2012; Bhaskaran et al., 2023). Furthermore, recent studies in business-to-investor marketing confirm that investors react to marketing signals during periods of high uncertainty, and that these signals actively shape their investment assessments (Nyilasy et al., 2025). Barth et al. (1998) demonstrate that published brand valuations possess incremental explanatory power for stock prices and returns, extending beyond traditional accounting metrics. Farhang et al. (2023) show that companies with high brand equity exhibited higher stock returns, lower volatility, and reduced systematic risk during the COVID-19 pandemic. These findings support the notion that brand equity serves a stabilizing and risk-mitigating function during periods of heightened uncertainty and may serve as relevant information for investment decisions.

Brand value rankings - such as those published by Interbrand, Brand Finance, or Kantar BrandZ - make brand values publicly visible. As standardized and easily accessible supplementary information, they act as observable signals that guide investor orientation. Furthermore, as qualitative information signals, they strengthen confidence in an investment's reliability and reduce uncertainty (Vazirani et al., 2023). Since trust positively influences both the likelihood of market participation and the amount of capital invested (Guiso et al., 2008), these rankings integrate three central mechanisms: information reduction through salient cues, signaling via publicly observable indicators, and trust-building as a psychological reinforcer of capital allocation decisions. Internally generated brands remain invisible on the balance sheet. Under both IFRS and US GAAP, there is a recognition prohibition for such assets, whereas acquired brands must be recorded at fair value (IAS 38.48, 38.63; IFRS 3.13; ASC 350, 805-20). This asymmetry creates a discrepancy between economic value and accounting visibility (Nichita, 2019). Brand value rankings bridge this information gap by providing publicly observable supplementary information. As external signals (Spence, 1973), they offer investors a point of orientation and an anchor for their investment assessments. Despite evidence that brand equity affects stock performance and can even serve as a basis for corporate financing (Sorrentino et al., 2025), little is known about how publicly visible brand value rankings shape portfolio decisions. Specifically, it remains unclear whether such rankings systematically favor top-tier brands, reduce diversification, or compensate for low brand awareness.

The present study addresses this research gap at the intersection of behavioral finance, brand valuation, and capital market research. It investigates how brand value rankings influence the investment decisions of private investors. The guiding research question is:

How does visibility of a brand value ranking change the way private investors build their stock portfolios?

Building on Signalling Theory and the Cue Utilization approach (Olson & Jacoby, 1972; Rao & Monroe, 1988), three hypotheses are derived: rankings shift allocations along the ranking structure (H1), reduce portfolio diversification (H2), and compensate for low brand awareness among lesser-known but highly ranked brands (H3). The thesis is structured as follows: Chapter 2 develops the theoretical framework and reviews the existing literature on the information content and effects of brand value rankings, as well as the hypotheses derived from it. Chapter 3 describes the data collection, sample, and methodological approach, including the experimental design. Chapter 4 presents the empirical analyses and results at the brand, group, and interaction levels. Finally, Chapter 5 summarizes the key findings, discusses their implications, and outlines limitations and avenues for

future research.

2. Literature review and theoretical framework

2.1 The Information Content of Brand Value Rankings

Brand value rankings - such as those by Interbrand and Brand Finance - are frequently utilized in both research and practice as indicators to quantify brand strength and its financial relevance. A vast body of research relies on data from these brand value rankings for empirical analysis. Numerous studies leverage this data to demonstrate robust correlations between brand values, capital market indicators, and corporate performance metrics. This suggests that these rankings provide substantial information content for investors (Barth et al., 1998; Kerin & Sethuraman, 1998; Madden et al., 2006; Fehle et al., 2008; Bhaskaran et al., 2023; Leite, 2024).

Bagna et al. (2017) investigated the explanatory power of brand valuations from Interbrand, Brand Finance, and BrandZ. Their findings indicate that published brand values correlate significantly with market capitalization and can serve as an informative basis for decision-making for investors. Leite (2024) provides further support for this view, identifying a strong link between brand equity and enterprise value. Furthermore, Laghi et al. (2022) demonstrate that accounting and market-specific metrics are significant predictors of brand valuations, emphasizing the growing relevance of integrating brand values into IFRS-based valuation models. From the perspective of capital market performance, Madden et al. (2006) demonstrate that strong brands, based on the Interbrand ranking, exhibit higher returns and lower risk. Over a seven-year period, the portfolio of the most valuable brands achieved a significantly positive risk-adjusted return with below-average volatility. Chehab et al. (2016) identify significantly higher cumulative abnormal returns (CAR) for Interbrand Top 100 companies and show that a higher ratio of brand value to market value is associated with these returns. Similarly, Hsu et al. (2013) report a sustained outperformance of Interbrand-listed companies compared to the S&P 500. Expanding on this, Voss and Mohan (2016) document that companies with highly valued brands generate abnormal returns in both bull and bear markets, underlining the stability and resilience of strong brands regardless of market direction. Analyses for Turkey (Bank et al., 2020) and Brazil (Oliveira et al., 2023) confirm that high brand values correlate with higher risk-adjusted returns, superior financial performance, and lower market risk. Regarding market reactions to the rankings, Dutordoir et al. (2015) show that the announcement of new Interbrand values triggers significant abnormal returns; on average, an increase in brand value raises enterprise value by 4%. These market reactions are especially strong in uncertain economic times, when investors are more cautious and risk-averse. Basgoze et al. (2016) also document positive abnormal returns following ranking publications, albeit with a time lag of approximately seven months. Shafi et al. (2018) interpret these ranking publications as market signals, although their findings remain inconsistent across different time windows. In summary, brand value rankings act as important economic signals. They can guide investment decisions and may help close the information gap between companies and investors.

2.2 Theoretical Framework and Hypothesis Development

The theoretical framework of this study combines two complementary mechanisms. Under incomplete information resulting from information costs (Grossman & Stiglitz, 1980), brand value rankings can act as publicly observable signals (Spence, 1973). Under bounded rationality, they can serve as salient cues that simplify complex valuation processes (Simon, 1955; Tversky & Kahneman, 1974; Olson & Jacoby, 1972). Based on this dual function as both signal and cue, the following hypotheses are derived:

First, rankings shift capital allocation along the rank structure through dual mechanisms. In markets that are not fully efficient due to information costs (Grossman & Stiglitz, 1980), observable signals serve to reduce information asymmetries (Spence, 1973). Since strong brands lower uncertainty, risk perception, and information costs (Voss & Mohan, 2016; Erdem & Swait, 2001; Srivastava et al., 1998; Madden et al., 2006), publicly visible brand value rankings are expected to act as condensed signals of quality and stability for investors. Simultaneously, from a behavioral perspective, these rankings function as cognitive cues. As simplifying valuation anchors, they direct allocations toward prominently placed brands (Olson & Jacoby, 1972; Tversky & Kahneman, 1974). The combination of a stronger signal and higher cognitive salience leads to two distinct effects: On the intensive margin (how much is invested), highly ranked brands should receive higher allocations due to their stronger quality signal. On the extensive margin (whether to invest at all), lower-ranked and unranked brands should be selected less frequently, as their absence or low visibility signals weaker quality or relevance (Spence, 1973).

H1: Participants exposed to a brand value ranking systematically reallocate capital along the ranking structure,

allocating more capital to higher-ranked brands (intensive margin) and reducing the likelihood of investing in lower-ranked and unranked brands (extensive margin), relative to a control group

Second, rankings narrow portfolio breadth through attention effects. The stronger cognitive salience of top-ranked brands likely narrows an investor's focus to a few highly visible stocks. This aligns with Behavioral Portfolio Theory, which suggests that investors often divide their investment capital into separate "mental layers" and fail to realize the benefits of diversification (Shefrin & Statman, 2000). Similarly, research on attention-driven investing (Barber & Odean, 2008) indicates that individuals tend to buy stocks that stand out. Therefore, the attention effect triggered by a ranking should lead to a less diversified portfolio, particularly by reducing investments in brands that lack ranking visibility.

H2: Participants exposed to a brand value ranking hold fewer distinct assets, leading to more concentrated and less diversified portfolios relative to the control group.

Third, rankings compensate for brand unfamiliarity through external orientation. The impact of the ranking as an external cue is likely influenced by how familiar an investor is with a brand. Due to the familiarity bias, investors tend to prefer companies they already know and trust (Huberman, 2001). However, according to the cue utilization literature, external cues gain importance precisely when prior knowledge is limited (Rao & Monroe, 1988). A brand value ranking can therefore partially compensate for a lack of brand awareness by providing external orientation when internal knowledge structures are absent. Following Keller (1993), brand awareness serves as an indicator of familiarity; well-known brands are perceived as less risky and provide a sense of security. For lesser-known brands, however, a high ranking position may serve as a substitute signal that reduces perceived uncertainty (Erdem & Swait, 2001).

H3: For lesser-known but highly ranked brands, participants exposed to the ranking allocate more capital than those in the control group, suggesting that rankings act as substitute signals for low brand awareness.

Additionally, we include subjective (self-assessed) investment knowledge as a covariate. Higher financial knowledge is generally associated with more informed portfolio choices and greater use of diversification (Lusardi & Mitchell, 2014). Subjective financial knowledge predicts prudent everyday financial behaviour and buffers financial anxiety beyond objective literacy (Lind et al., 2020). In line with evidence linking decision-making competence to more bias-resistant choices (Parker & Fischhoff, 2005), we also explore whether investment knowledge moderates the ranking effect (Group \times Knowledge); this test is exploratory rather than a formal hypothesis.

3. Data gathering, variables and methodology

3.1 Data Gathering and Sample Description

The data on investment behavior were collected via an online experiment. The study focuses on the impact of a specific brand value ranking treatment, with details on its design provided in the next section. Participants were randomly assigned to one of two groups. While both groups performed the same investment task, the treatment group also received brand value information in the form of a ranking (see Section 3.2). To create a realistic decision context, the experiment used a portfolio allocation task (Batsell & Louviere, 1991; Costa, 2019). The questionnaire was refined through a pretest with three academic experts and twelve private investors. This process improved the survey's clarity and realism while also calibrating the measurement instrument (Hulland et al., 2018). Incomplete responses were removed (Jamshidian, 2009), leaving a final sample of 244 respondents. *Table 1* displays their demographic profile.

Tab. 1: Demographic data of the respondents

Variable (All groups)	n	Mean	S.E.	Median	σ	KS-statistic
AGE (all)	244	30.012	0.581	27.000	9.081	0.182
AGE (male)	102	31.863	0.942	29.000	9.511	0.138
AGE (female)	142	28.683	0.717	26.000	8.547	0.215
Variable (Group 0)	n	Mean	S.E.	Median	σ	KS-statistic
AGE (all)	121	29.545	0.815	27.000	8.966	0.174
AGE (male)	49	30.245	1.243	29.000	8.698	0.144
AGE (female)	72	29.069	1.081	25.500	9.173	0.228
Variable (Group 1)	n	Mean	S.E.	Median	σ	KS-statistic
AGE (all)	123	30.472	0.830	27.000	9.206	0.191
AGE (male)	53	33.358	1.381	31.000	10.056	0.158
AGE (female)	70	28.286	0.944	26.000	7.898	0.200

Employment status	All		Male		Female	
	Abs.	in %	Abs.	in %	Abs.	in %
Full time employed	115	47.131	69	67.647	46	32.394
Part time employed	27	11.066	10	9.804	17	11.972
Non-working parent	4	1.639	0	0.000	4	2.817
Pupil	11	4.508	4	3.922	7	4.930
Student	85	34.836	19	18.627	66	46.479
Retired	1	0.410	0	0.000	1	0.704
Other	1	0.410	0	0.000	1	0.704
Total	244	100	102	100	142	100

To ensure the comparability of the randomized groups, **balance tests** were conducted for key demographic variables. No significant difference was found between the groups regarding **age** ($Z = -0.903$, $p = .366$) or **gender**, $\chi^2(1, N = 244) = 0.17$, $p = .681$. The gender distribution was similar in both groups: the control group (Group 0) included 49 men and 72 women, while the treatment group (Group 1) included 53 men and 70 women. Furthermore, there was no significant difference in **self-reported investment knowledge** (KNOWLEDGE¹), ($F = .026$, $p = .872$).

For the investigation of brand-related allocations, subjective knowledge is the more theoretically appropriate construct for this survey. Investors decide primarily based on their perceived competence rather than objective knowledge tests, which are not present in the actual decision-making situation. This subjective assessment forms the psychological basis for decision certainty; Hadar et al. (2013) demonstrate that subjective knowledge significantly influences willingness to invest, independent of objective financial knowledge, particularly when individuals perceive themselves as relatively knowledgeable. Similarly, Allgood & Walstad (2016) show that perceived literacy is often a stronger predictor of behavior than objective facts. Netemeyer et al. (2024) provide evidence that changes in financial behavior following financial education are primarily mediated by subjective financial knowledge, while changes in objective knowledge show negligible mediating effects.

3.2 Experimental Design

In the experiment, participants were asked to construct a hypothetical investment portfolio consisting of 20 branded companies. All participants ($N = 244$) were presented with the same set of 20 companies. Of these, 15 were included in the ranking shown to the treatment group (see Figure 1). The remaining five companies (Douglas, Lidl, Škoda, Hard Rock Cafe, and Calvin Klein) did not appear in the ranking and served as unranked comparison brands. The treatment group (Group 1) was presented with an adapted brand value ranking stimulus based on Brand Finance data. The stimulus consisted of a purposive selection of 15 brands from various rank

¹ Definition of Investment Knowledge: In this study, investment knowledge refers to an individual's self-assessed expertise regarding investments - specifically, their perceived competence in evaluating financial information and making investment decisions.

positions. This selection made it possible to integrate both globally prominent and lesser-known brands into the same decision-making context. To ensure transparency, the original rank positions were displayed in the figure; any omitted ranks are the result of intentional selection rather than missing data. This created a visible adjusted ranking from 1 to 15, sorted in ascending order of brand value. The control group (Group 0) received no ranking, while having the same investment options available.

Participants were explicitly informed that they could freely allocate their budget across all 20 companies, regardless of whether they were publicly traded. This approach was chosen because prominent brand value rankings include both listed and non-listed firms, thereby reflecting 'ranking reality.' The objective was not to replicate a live trading environment, but to create a standardized decision context to observe how the ranking affects capital allocation. Participants were not required to invest in every brand; they could choose to skip any company by entering '0', effectively resulting in a zero investment for that specific brand. The total selection was simply limited to the provided set of 20 companies.

The participants' task was to make a hypothetical investment of €100,000 by allocating their capital across the 20 companies in percentage shares (0% to 100%). The original instruction read:

“You have €100,000 to invest. Please enter in each box what percentage of your budget you would like to invest in the following brands (use whole numbers). Please allocate your budget in full. Your current sum will be displayed at the bottom of this page. You are completely free in how you distribute your funds. Examples: 20% = €20,000; 10% = €10,000, etc.”

The sum of all individual allocations had to equal exactly 100%. To ensure a standardized decision-making environment and mitigate UI-driven attention biases, the digital layout of the questionnaire was kept strictly identical for both groups, with the sole exception of the visual ranking stimulus for Group 1. Below the standardized instruction text, all 20 companies were presented simultaneously in a vertically scrollable list. For each company, a standardized numeric input field was provided next to the brand name (investment in %). To assist participants, a total sum field at the bottom of the list required the final allocation to equal exactly 100% (Tab. 15; appendix). For the treatment group (Group 1), the ranking graphic with 15 companies (Fig. 1) was statically displayed directly above the input list.

The dependent variable is the percentage of the budget assigned to each company by the respondent. Thus, a respondent's total allocation can be represented as follows:









$$Portfolioweighting_i = \sum_{j=1}^{20} a_{ij} = 100 \%$$

whereas $i = \{1, \dots, 244\}$; $0 \% \leq a_{ij} \leq 100 \%$

To ensure methodological robustness, several control mechanisms were implemented within the online questionnaire:

- a) Portfolio Validation: An integrated validation routine ensured that the sum of the percentage allocations equaled exactly 100%. Participants could only proceed to the next page once this condition was met.
- b) Randomized Group Assignment: Participants were randomly assigned to either the treatment or the control group to prevent systematic bias.
- c) Randomization of the Company List: To eliminate order effects, the presentation order of the 20 companies was individually randomized for each participant.

Fig. 1: Adapted brand value ranking stimulus based on selected positions from Brand Finance

Rank	Logo	Brand	Brand Value
1		Apple	\$263,375M
2		Amazon	\$254,188M
8		ICBC	\$72,788M
9		Verizon	\$68,890M
13		Mercedes-Benz	\$58,225M
14		Tencent	\$56,432M
17		Ping An	\$54,579M
20		Home Depot	\$52,917M
22		Disney	\$51,244M
38		McDonald's	\$33,838M
39		Coca-Cola	\$33,166M
47		Nike	\$30,443M
50		UPS	\$30,056M
90		Mastercard	\$19,117M
98		SAP	\$17,992M

4. Analyses and empirical results

4.1 Analysis of Brand-Specific Allocations

The analysis of investment behavior was first conducted at the brand level. Tables 2 and 3 provide a descriptive overview of the inclusion frequency and the average portfolio weights for each group. To robustly assess the differences between groups, classical F-statistics, the Welch test (Rasch et al., 2011), and the non-parametric Mann-Whitney U test were employed.

Tab. 2: Descriptive statistics & test for differences for the weighting of individual brands: incl. 0-Investments: Extensive Margin

Company	Group	n	Mean	S.E.	Median	σ	KS-statistic	F-statistic		
								F-statistic (t-Test)	(Welch Test)	Z-statistic (U-Test)
APPLE	0	121	13.983	1.020	10.000	11.215	.151	3.364*	3.370*	-1.780*
	1	123	16.797	1.144	20.000	12.688	.181			
AMAZON	0	121	15.769	1.101	15.000	12.113	.198	.180	.181	-.933
	1	123	16.431	1.103	20.000	12.236	.135			
ICBC	0	121	1.413	.312	.000	3.437	.403	1.212	1.216	-.255
	1	123	1.959	.384	.000	4.261	.425			
VERIZON	0	121	1.942	.359	.000	3.950	.366	1.001	1.007	-.337
	1	123	2.577	.521	.000	5.782	.396			
MERCEDES-BENZ	0	121	7.165	1.028	5.000	11.311	.263	.366	.364	-.065
	1	123	6.431	.653	5.000	7.240	.211			
TENCENT	0	121	1.818	.379	.000	4.165	.429	.678	.680	-.479
	1	123	2.298	.446	.000	4.946	.411			
PING-AN	0	121	.702	.198	.000	2.174	.461	.330	.331	-.247
	1	123	.878	.233	.000	2.579	.487			
HOME-DEPOT	0	121	1.058	.187	.000	2.059	.424	3.874**	3.922**	-.011
	1	123	2.098	.491	.000	5.440	.398			
DISNEY	0	121	6.868	.799	5.000	8.793	.237	.005	.005	-.716
	1	123	6.959	1.041	3.000	11.544	.273			
MCDONALDS	0	121	5.116	.940	2.000	10.340	.310	.010	.010	-2.040**

	1	123	4.959	<i>1.231</i>	.000	13.655	.358			
COCA-COLA	0	121	6.124	<i>.614</i>	5.000	6.751	.219			
	1	123	6.374	<i>.720</i>	5.000	7.985	.227	.070	.070	-.408
NIKE	0	121	6.050	<i>.604</i>	5.000	6.643	.216	4.654**	4.648**	-2.644***
	1	123	4.285	<i>.553</i>	.000	6.130	.311			
UPS	0	121	3.917	<i>.510</i>	1.000	5.612	.245			
	1	123	3.224	<i>.529</i>	.000	5.862	.335	.891	.892	-1.829*
MASTERCARD	0	121	5.058	<i>.546</i>	5.000	6.002	.222			
	1	123	5.545	<i>.730</i>	2.000	8.096	.247	.284	.285	-.147
SAP	0	121	11.223	<i>1.139</i>	8.000	12.530	.185			
	1	123	10.358	<i>1.238</i>	7.000	13.729	.225	.264	.265	-1.005
DOUGLAS	0	121	1.587	<i>.236</i>	.000	2.591	.375			
	1	123	1.224	<i>.310</i>	.000	3.443	.436	.865	.869	-2.530**
LIDL	0	121	4.595	<i>.756</i>	.000	8.319	.290			
	1	123	3.472	<i>.522</i>	.000	5.792	.343	1.503	1.494	-1.293
SKODA	0	121	2.430	<i>.455</i>	.000	5.006	.339			
	1	123	2.220	<i>.438</i>	.000	4.853	.400	.111	.111	-.995
HARDROCKCAFE	0	121	1.347	<i>.274</i>	.000	3.016	.367			
	1	123	.943	<i>.222</i>	.000	2.461	.462	1.317	1.312	-2.017**
CALVINKLEIN	0	121	1.835	<i>.290</i>	.000	3.189	.346			
	1	123	.974	<i>.234</i>	.000	2.594	.443	5.336**	5.318**	-2.910***

Note: Notes: Group 0 = Group without the brand value ranking; Group 1 = Group with brand value rankings (Treatment Group). A line was drawn after SAP. The brands from the top up to SAP were represented in the ranking for Group 1 (see Fig. 1), while the five brands below the line were not included. * 10 percent level; ** 5 percent level; *** 1 percent level.

Tab. 3: Descriptive statistics & test for differences for the weighting of individual brands: > 0-Investments: Intensive Margin

Company	Group	n	Mean	S.E.	Median	σ	KS-statistic	F-statistic		
								F-statistic (t-Test)	(Welch Test)	Z-statistic (U-Test)
APPLE	0	99	17.091	1.001	15.000	10.017	.184	5.113**	5.123**	-2.360**
	1	101	20.455	1.093	20.000	10.991	.249			
AMAZON	0	105	18.171	1.092	15.000	11.190	.245	2.228	2.240	-2.358**
	1	99	20.414	1.026	20.000	10.210	.163			
ICBC	0	31	5.516	.877	5.000	4.884	.284	3.101*	3.101*	-1.988*
	1	31	7.774	.935	8.000	5.207	.173			
VERIZON	0	39	6.026	.785	5.000	4.902	.250	4.917**	4.639**	-2.152**
	1	34	9.323	1.315	6.500	7.666	.214			
MERCEDES-BENZ	0	78	11.115	1.409	10.000	12.446	.305	.069	.071	-1.094
	1	74	10.689	.748	10.000	6.438	.326			
TENCENT	0	29	7.586	1.000	5.000	5.389	.202	.729	.737	-.707
	1	32	8.844	1.069	7.000	6.049	.206			
PING-AN	0	20	4.250	.836	4.000	3.740	.271	1.994	1.985	-1.655*
	1	18	6.000	.918	5.000	3.896	.268			
HOME-DEPOT	0	33	3.879	.374	5.000	2.147	.275	9.093***	8.603***	-2.213**
	1	31	8.323	1.468	5.000	8.175	.271			
DISNEY	0	78	10.653	1.010	9.000	8.924	.286	1.333	1.261	-1.484
	1	67	12.776	1.597	10.000	13.073	.271			
MCDONALDS	0	66	9.379	1.541	6.000	12.522	.344	1.223	1.070	-.718
	1	48	12.708	2.826	8.000	19.582	.347			
COCA-COLA	0	79	9.380	.704	8.000	6.260	.245	3.052*	2.977*	-1.852*
	1	69	11.362	.908	10.000	7.542	.238			
NIKE	0	79	9.266	.691	7.000	6.141	.288	.090	.092	-.728
	1	55	9.582	.777	10.000	5.763	.307			
UPS	0	62	7.645	.729	5.000	5.743	.274	.669	.638	-.753
	1	46	8.630	.994	6.000	6.744	.267			
MASTERCARD	0	70	8.743	.654	7.500	5.474	.238	2.501	1.988	-1.412
	1	65	10.492	1.054	10.000	8.498	.323			
SAP	0	87	15.610	1.312	10.000	12.239	.199	.024	.024	-.086
	1	80	15.925	1.586	10.000	14.188	.249			
DOUGLAS	0	43	4.465	.374	5.000	2.453	.284	2.658	1.849	-0.381
	1	25	6.040	1.096	5.000	5.481	.255			
LIDL	0	58	9.586	1.293	6.500	9.849	.294	.093	.102	-.537
	1	47	9.085	.886	10.000	6.071	.218			
SKODA	0	42	7.000	.983	5.000	6.371	.290	.111	.111	-.819
	1	34	8.029	1.071	5.000	6.245	.229			
HARDROCKCAFE	0	37	4.405	.667	5.000	4.058	.361	.391	.422	-.707
	1	23	5.043	.721	5.000	3.457	.201			
CALVINKLEIN	0	45	4.933	.776	5.000	3.883	.315	.022	.020	-.320
	1	25	4.800	.430	5.000	3.601	.359			

Two complementary analyses were conducted to examine the ranking's impact on the weighting of individual companies: (a) an analysis including all cases (i.e., including zero investments) and (b) an analysis focusing solely on positive investments (invest > 0). This approach distinguishes between the **extensive margin** - representing the unconditional allocation and the decision of whether to invest at all - and the **intensive margin**, which acts as a conditional allocation measuring the investment amount once a decision to invest has been made. This distinction is central to the interpretation, as the ranking does not necessarily influence both levels in the same way.

(a) Analysis including zero investments: extensive margin (Table 2). Regarding the brands included in the ranking, the treatment group (Group 1) shows higher mean values for 8 out of the 10 highest-ranked brands. However, inferential statistics reveal significant differences only for Apple, McDonald's, and Home Depot. In the lower range, particularly for the five unranked comparison brands, the mean values are consistently

higher in Group 0; for three out of these five brands (Douglas, Hard Rock Café, and Calvin Klein), the differences are significant. Overall, this pattern suggests that the group with access to the ranking considers unranked brands less frequently and aligns its allocation more strongly toward the brands visible in the ranking.

- (b) Analysis of investments > 0 only: Intensive margin (Table 3). When zero investments are excluded, the differences for the unranked brands disappear. This suggests that the differences previously observed for these brands were primarily driven by the decision not to invest at all. At the same time, more pronounced differences emerge for the high-ranked brands: for 4 of the top 5 and 6 of the top 10 brands, the treatment group shows significantly higher allocations. This indicates that participants with access to the ranking concentrate their positive investments more heavily on the high-signal top brands.

Taken together, the ranking operates on two levels: at the extensive margin, it acts as a selection filter that reduces the likelihood of investment in unranked and lower-ranked brands; at the intensive margin, it concentrates positive investments more heavily on top-ranked brands. In the next step, the investment decision was analyzed at a binary level (0 = not invested, 1 = invested), regardless of the specific allocation amount. The focus was placed on the unranked comparison brands as well as those positioned at the lower end of the ranking (positions 10–15). This perspective is exploratory in nature and centers on the fundamental decision of whether or not to invest, rather than on the magnitude of the investment.

Tab. 4: Chi² Tests and odds Ratios for binary investment decisions: Unranked brands and ranks 10-15

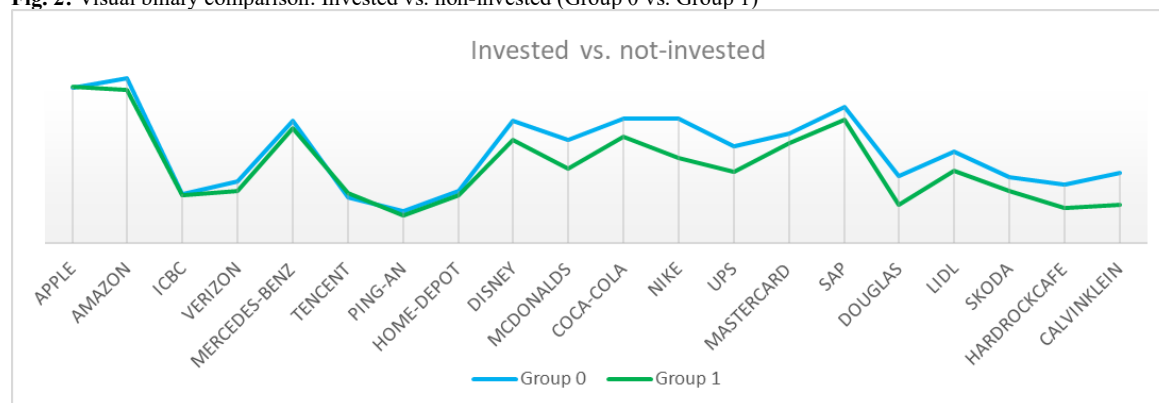
Brands (not ranked)	Gr	n	% invested	χ^2 (df=1)	OR	Interpretation	95%-CI
Calvin Klein	0	121	37,2%	8.480***	.431	Group 0 \approx 2.32x higher odds of investing	[.243; .764]
	1	123	20,3%	p=.004			
Hard Rock Café	0	121	30,6%	4.642**	.522	Group 0 \approx 1.92x higher odds of investing	[.288; .947]
	1	123	18,7%	p=.031			
Douglas	0	121	35,5%	7.022***	.463	Group 0 \approx 2.16x higher odds of investing	[.260; .823]
	1	123	20,3%	p=.008			
Lidl	0	121	47,9%	2.352	.672	Group 0 \approx 1.49x higher odds of investing	[.404; 1.118]
	1	123	38,2%	p=.125			
Skoda	0	121	34,7%	1.421	.719	Group 0 \approx 1.39x higher odds of investing	[.412; 1.238]
	1	123	27,6%	p=.233			

Brands ranked 10-15	Gr	n	% invested	χ^2 (df=1)	OR	Interpretation	95%-CI
McDonalds	0	121	54,5%	5.903** <i>p</i> =.015	.533	Group 0 \approx 1.88x higher odds of investing	[.321; .887]
	1	123	39,0%				
Coca Cola	0	121	65,3%	2.159 <i>p</i> =.142	.679	Group 0 \approx 1.47x higher odds of investing	[.405; 1.139]
	1	123	56,1%				
Nike	0	121	65,3%	10.428*** <i>p</i> =.001	.430	Group 0 \approx 2.32x higher odds of investing	[.257; .721]
	1	123	44,7%				
UPS	0	121	51,2%	4.737** <i>p</i> =.030	.568	Group 0 \approx 1.76x higher odds of investing	[.341; .947]
	1	123	37,4%				
Mastercard	0	121	57,9%	.618 <i>p</i> =.432	.813	Group 0 \approx 1.22x higher odds of investing	[.491; 1.348]
	1	123	52,8%				
SAP	0	121	71,9%	1.329 <i>p</i> =.249	.727	Gruppe 0 \approx 1.38x higher odds of investing	[.423; 1.251]
	1	123	65,0%				

Note: The Pearson χ^2 test (df = 1) tests for group differences in the investment decision (invested vs. not invested). The effect size is reported as an Odds Ratio (OR) with a 95% confidence interval (CI). The OR is defined as OR = Odds(Group 1) / Odds(Group 0); thus: OR < 1 indicates lower odds in Group 1 (or higher odds in Group 0; factor = 1/OR), while OR > 1 indicates higher odds in Group 1 relative to Group 0. P-values: *** p < .01, ** p < .05, * p < .10.

When looking at these results visually (Fig. 2) - focusing only on the 'yes or no' investment decision - the lines for both groups start out almost the same. However, after the top 10 brands, they begin to move apart: the line for Group 1 stays consistently below Group 0. This shows that for brands further down the list, participants in the treatment group were less likely to invest at all, regardless of the amount.

Fig. 2: Visual binary comparison: Invested vs. non-invested (Group 0 vs. Group 1)



The results in Table 4 show that for unranked brands - especially Calvin Klein, Hard Rock Café, and Douglas - participants in the control group were much more likely to invest than those in the treatment group. A similar trend can be seen for Lidl and Škoda. This pattern also appears, though less strongly, for brands at the bottom of the ranking (10-15): control group participants invested significantly more often in McDonald's, Nike, and UPS, while there were no significant differences for Coca-Cola, Mastercard, and SAP. This binary analysis supports the earlier findings on the intensive margin. It shows that the ranking selectively reduces the chance of an investment, particularly for unranked and lower-placed brands. From this point of view, the ranking acts mainly as a selection filter for brands that send weaker signals or no signals at all.

4.2 Brand Awareness and Allocation: The Role of Familiarity

The following analysis focuses on cases where the brand was unknown. As outlined in the derivation of H3, the effect of the ranking as an external cue should be particularly evident here, as there are no established knowledge structures based on brand awareness (Rao & Monroe, 1988; Keller, 1993; Erdem & Swait, 2001).

This analysis focuses on five lesser-known brands, whose lack of familiarity within the sample is shown in the table below (Tab. 5). These five brands were previously identified as unfamiliar in the pretest and were intentionally included in the study design to examine the ranking's impact even when brand familiarity is low. A minimum threshold of 20% 'unknown' was established to ensure a sufficient sample size for statistical group comparisons. Brands with very high awareness were excluded from this sub-analysis (Tab. 14; appendix). For each brand, the analysis considered only those participants who were unfamiliar with the brand. Within this subgroup, a distinction was again made between Group (0) participants without the ranking treatment and Group (1) participants with the ranking treatment. Furthermore, the extensive (ext.) and intensive (int.) margin perspectives were compared once again.

Tab. 5: The five lesser-known brands

Relative Rank Position	Brand	Not Known
3	ICBC	220 (90,2%)
4	VERIZON	180 (73,8%)
6	TENCENT	201 (82,4%)
7	PINGAN	234 (95,9%)
8	HOMEDEPOT	138 (56,6%)

Note: The rankings used (1-15) refer to the relative position within the selection. This internal numbering is independent of the original positions in the global Brand Finance overall ranking.

Tab. 6: Investment differences regarding lesser-known brands

Stock	Group	n	Mean	S.E.	Median	σ	KS-statistic	T-statistic (t-test)	Z-statistic (U-Test)
ICBC ext.	0 not known	110	1.281	.292	.000	3.065	.417	-.983	-.136
	1 not known	110	1.754	.382	.000	4.007	.451	(<i>p</i> =.327)	(<i>p</i> =.892)
ICBC int.	0 not known	27	5.222	.817	5.000	4.245	.299	-2.218**	-2.275**
	1 not known	24	8.042	.986	10.000	4.831	.199	(<i>p</i> =.031)	(<i>p</i> =.023)
VERIZON ext.	0 not known	93	.720	.189	.000	1.826	.449	-1.663*	-.152
	1 not known	87	1.735	.580	.000	5.412	.430	(<i>p</i> =.099)	(<i>p</i> =.879)
VERIZON int.	0 not known	19	3.526	.589	3.000	2.568	.178	-2.255**	2.365**
	1 not known	17	8.882	2.300	5.000	9.486	.277	(<i>p</i> =.037)	(<i>p</i> =.018)
TENCENT ext.	0 not known	102	0,892	.310	.000	3.130	.455	-.322	-.210
	1 not known	99	1.030	.296	.000	2.953	.475	(<i>p</i> =.748)	(<i>p</i> =.834)
TENCENT int.	0 not known	16	5.687	1.518	5.000	6.074	.358	-.363	-1.227
	1 not known	16	6.375	1.136	5.000	4.544	.306	(<i>p</i> =.720)	(<i>p</i> =.220)
PINGAN ext.	0 not known	118	.636	.195	.000	2.127	.465	-.672	-.340
	1 not known	116	.845	.242	.000	2.613	.497	(<i>p</i> =.502)	(<i>p</i> =.734)
PINGAN int.	0 not known	18	4.166	.929	2.500	3.944	.250	-1.699*	-1.948**
	1 not known	15	6.533	1.041	5.000	4.033	.248	(<i>p</i> =.099)	(<i>p</i> =.051)
HOMEDEPOT ext.	0 not known	76	.986	.231	.000	2.017	.425	-1.216	-.366
	1 not known	62	1.983	.787	.000	6.195	.400	(<i>p</i> =.228)	(<i>p</i> =.715)
HOMEDEPOT int.	0 not known	20	3.750	.507	5.000	2.268	.259	-2.042*	-.865
	1 not known	14	8.786	2.875	5.000	10.757	.423	(<i>p</i> =.049)	(<i>p</i> =.387)

Note: The t-statistic reflects the t-value documented after conducting Levene's test. If Levene's test was significant, the t-value for 'equal variances not assumed' is reported. The analysis of the extensive margin (abbr. ext.) is compared to the intensive margin (abbr. int.).

The results consistently show higher average investment values in the treatment group among participants who were unfamiliar with the respective brands. At the same time, the absolute level of investment in these brands remains moderate. This suggests that the ranking does not trigger exceptionally high allocations, but rather leads to a relative revaluation of unknown yet highly-ranked brands. When considering total values (including zero investments), the differences are mostly non-significant, though they do show a consistent descriptive trend. The pattern becomes significantly clearer at the intensive margin: several brands - most notably ICBC, Verizon, and to some extent Home Depot - show significantly higher allocations in the treatment group. This suggests that the

ranking can partially compensate for a lack of brand awareness, providing orientation as an external cue for unknown brands. Since the investigated brands were ranked relatively high, it is plausible that this visible placement further amplified their signaling effect. Thus, for unknown brands, the impact of the ranking unfolds primarily on the intensive margin. Given the small size of the unknown-only subsamples for the intensive-margin analyses (between 14-20 participants per group), we regard these findings as preliminary and exploratory. To enhance robustness and reduce idiosyncratic noise, we therefore also report complementary aggregated results at the bucket level 'Lesser Known Brands' (Tab. 8).

4.3 Aggregated Bucket-Level Analysis

To reveal patterns in portfolio allocation beyond individual brands, companies were aggregated into analytical groups ('buckets') based on the ranking structure of the stimulus. This approach follows the logic of characteristic-sorted portfolios, where units are grouped along an ordered dimension of characteristics. This aggregation serves to minimize idiosyncratic noise specific to individual brands and provides a more stable basis for estimation (Cattaneo et al., 2020). This method allows for the investigation of treatment effects as robust relationships at the level of substantively homogeneous brand groups.

It is important to note that the labels '1–5,' '6–10,' and '11–15' refer to the relative positions within the 15 ranking brands included in the stimulus, rather than the original ranks in the full Brand Finance ranking. In addition, an 'unranked' bucket (Douglas, Lidl, Škoda, Hard Rock Café, Calvin Klein) and an exploratory 'lesser-known' cluster were formed. Building on the previous individual analysis, the latter aggregates these five brands into a single cluster to test the robustness of the observed effects. Unlike the ranking buckets, the 'lesser-known' cluster is not based on stimulus rank position but on the empirically observed low brand familiarity.

Methodologically, these buckets were analyzed using both the weighting perspective (extensive and intensive margin, see Section 4.1) and the quantity perspective (number of positively weighted titles). This approach makes it possible to distinguish whether the ranking primarily influences the breadth of the investment decision or alters the intensity of the allocation.

Tab. 6: Tests for differences by group: weighting of selected brands incl. 0-Investments: Extensive margin

Grouped PORTFOLIO RANK (Weighting)	Gr.	Mean	S.E.	Median	σ	KS- statistic	F-statistic (t-Test)	F-statistic (Welch Test)	Z-statistic (U-Test)
1 to 5 ranked brands	0	40.273	1.789	40.000	19.682	.134	2.273	2.275	-2.068**
	1	44.195	1.887	45.000	20.931	.114	(<i>p</i> =.133)	(<i>p</i> =.133)	(<i>p</i> =.039)
6 to 10 ranked brands	0	15.562	1.202	15.000	13.217	.137	.640	.643	-.197
	1	17.187	1.631	15.000	18.088	.171	(<i>p</i> =.424)	(<i>p</i> =.423)	(<i>p</i> =.844)
11 to 15 ranked brands	0	32.372	1.418	30.000	15.603	.106	1.397	1.401	-1.368
	1	29.789	1.659	30.000	18.398	.102	(<i>p</i> =.238)	(<i>p</i> =.238)	(<i>p</i> =.171)
Unranked brands	0	11.793	1.117	10.000	12.289	.170	4.212**	4.198**	-1.973**
	1	8.837	.913	5.000	10.123	.272	(<i>p</i> =.041)	(<i>p</i> =.042)	(<i>p</i> =.048)
1 to 10 ranked brands	0	55.835	1.772	55.000	19.491	.110	4.579**	4.584**	-2.331**
	1	61.382	1.890	60.000	20.963	.139	(<i>p</i> =.033)	(<i>p</i> =.033)	(<i>p</i> =.022)
Lesser known brands	0	6.933	.845	2.000	9.302	.268	3.504*	3.527*	-.794
	1	9.813	1.278	2.000	14.181	.251	(<i>p</i> =.062)	(<i>p</i> =.062)	(<i>p</i> =.427)

Tab. 7: Tests for differences by group: weighting of selected brands, investments >0: Intensive margin

Grouped PORTFOLIO RANK (Weightning > 0)	Gr.	N	Mean	S.E.	Median	σ	KS-statistic	F-statistic (t-Test)	F-statistic (Welch Test)	Z-statistic (U-Test)
1 to 5 ranked brands	0	115	42.374	1.663	40.000	17.831	.162	2.881*	2.883*	-2.220**
	1	117	46.462	1.741	45.000	18.830	.135	(<i>p</i> =.091)	(<i>p</i> =.091)	(<i>p</i> =.026)
6 to 10 ranked brands	0	100	18.830	1.223	20.000	12.230	.182	3.708*	3.603*	-1.843*
	1	92	22.989	1.818	20.000	17.437	.213	(<i>p</i> =.056)	(<i>p</i> =.059)	(<i>p</i> =.065)
11 to 15 ranked brands	0	117	33.479	1.354	30.000	14.646	.124	.411	.410	-.896
	1	114	32.140	1.593	30.000	17.005	.120	(<i>p</i> =.522)	(<i>p</i> =.523)	(<i>p</i> =.370)
Unranked brands	0	80	17.838	1.226	15.000	10.964	.115	.711	.753	-.488
	1	66	16.470	.990	15.500	8.045	.138	(<i>p</i> =.401)	(<i>p</i> =.387)	(<i>p</i> =.625)
1 to 10 ranked brands	0	119	56.773	1.672	56.000	18.238	.099	5.317**	5.323**	-2.405**
	1	121	62.405	1.779	60.000	19.564	.123	(<i>p</i> =.022)	(<i>p</i> =.022)	(<i>p</i> =.016)
Lesser known brands	0	61	13.754	1.129	10.000	8.116	.173	6.922***	6.975***	-2.089**
	1	62	19.467	1.846	15.500	14.533	.168	(<i>p</i> =.010)	(<i>p</i> =.010)	(<i>p</i> =.037)

Tab. 8: Tests for differences by group: quantity of selected brands

Grouped PORTFOLIO RANK (Quantity)	Gr.	Mean	S.E.	Median	σ	KS-statistic	F-statistic (t-Test)	F-statistic (Welch Test)	Z-statistic (U-Test)
1 to 5 ranked brands	0	2.909	.122	3.000	1.342	0.184	.802	.802	-.856
	1	2.756	.120	3.000	1.327	0.167	(<i>p</i> =.371)	(<i>p</i> =.371)	(<i>p</i> =.392)
6-10 ranked brands	0	1.868	.139	2.000	1.527	0.218	1.878	1.876	-1.196
	1	1.610	.127	1.000	1.412	0.187	(<i>p</i> =.172)	(<i>p</i> =.172)	(<i>p</i> =.232)
11-15 ranked brands	0	3.116	.143	3.000	1.577	0.181	8.044***	8.035***	-2.683***
	1	2.561	.133	2.000	1.477	0.185	(<i>p</i> =.005)	(<i>p</i> =.005)	(<i>p</i> =.007)
Unranked brands	0	1.860	.172	1.000	1.890	0.229	7.526***	7.502***	-2.418**
	1	1.252	.140	1.000	1.555	0.253	(<i>p</i> =.007)	(<i>p</i> =.007)	(<i>p</i> =.016)
1 to 10 ranked brands	0	4.777	.242	4.000	2.657	0.152	1.601	1.598	-1.055
	1	4.366	.218	4.000	2.413	0.170	(<i>p</i> =.207)	(<i>p</i> =.207)	(<i>p</i> =.291)
Lesser known brands	0	1.256	.155	1.000	1.710	.270	.108	.108	-.101
	1	1.187	.141	1.000	1.569	.271	(<i>p</i> =.742)	(<i>p</i> =.742)	(<i>p</i> =.919)

Note: The table is structured in the same way as Tab. 2. Group 0 = Group without brand value ranking; Group 1 = Group with brand value ranking. Lesser known: The 5 Brands which have been "lesser known" were put into a separate bucket: ICBC, VERIZON, TENCENT, PINGAN, HOMEDEPOT.

In the analysis including zero investments, the treatment group shows a significantly higher weighting for Top 1–10 brands and significantly lower weightings for unranked brands. A directional effect of the same nature is observed for Top 1-5, while no significant differences emerge for the 6-10 and 11-15 buckets. Overall, this suggests that the ranking shifts allocation toward higher-ranked brands and displaces unranked alternatives. When excluding zero investments, the effect for Top 1-10 remains significant; for Top 1-5, a positive effect in favor of the treatment group is again observed. The difference for unranked brands disappears, suggesting that this effect primarily arises from the initial investment decision (yes/no). Additionally, a significant group difference emerges within the 'lesser-known' bucket. This is consistent with the assumption and previous analysis that the ranking can serve as a cue for unfamiliar but highly-ranked brands.

The quantity analyses at the bucket level provide additional insights into portfolio breadth. The treatment group holds significantly fewer positions in the '11-15' and 'unranked' buckets. No significant differences in the number of positive positions were found for the 'Top 1-5,' 'Top 6-10,' 'Top 1-10,' or 'lesser-known' buckets. Overall, the ranking makes the portfolio structure more selective: lower-ranked and unranked brands are included less frequently, while the number of positions in the top buckets does not significantly increase. Taken together, the

bucket analyses demonstrate that the ranking treatment operates on two levels: it shifts allocation in favor of higher-ranked brands and reduces the inclusion of unranked or lower-ranked brands

4.4 Interaction Analysis: The Role of Investment Knowledge

The inclusion of investment knowledge as a covariate (Model 2) and the mean-centered interaction term 'Group × Knowledge' (Model 3; Aiken et al., 1991; Cohen et al., 2013; Dawson, 2014) shows that the group effects remain largely stable (Tab. 11,12,13).

Tab. 10: Self-assessed investment knowledge across groups

	Group	n	Mean	S.E.	Median	σ
KNOWLEDGE	Group 0	121	4.463	.236	4.000	2.592
	Group 1	123	4.439	.244	4.000	2.701

Note: KNOWLEDGE: How would you rate your investment knowledge (capital assets/ investments)? (1 = no knowledge at all; 10 = very high level of knowledge)

For weighting, the group effects remain largely stable across all models. Effects that were already significant or marginally significant in Model 1 persist after the inclusion of investment knowledge (Model 2) and the 'Group × Knowledge' interaction (Model 3) - on both the extensive and intensive margins (Tab. 11/12). This suggests that the ranking's impact on weighting operates predominantly independent of the participants' level of knowledge.

Moderation (Exception): Bucket 11-15. At mean-centered investment knowledge, no significant group effect is observed, neither on the extensive margin ($F(1, 240) = 1.41, p = .236$) nor on the intensive margin ($F(1, 227) = 0.48, p = .489$). Instead, knowledge-related effects emerge: on the extensive margin, there is a positive main effect of knowledge ($F(1, 240) = 4.90, p = .028$) and a marginal interaction ($F(1, 240) = 3.58, p = .060$), which is significant in the robust coefficient test ($b = -1.55, HC3-SE = 0.74, t(240) = -2.09, p = .037$). On the intensive margin, a marginal knowledge effect ($F(1, 227) = 3.04, p = .083$) and a significant interaction ($F(1, 227) = 4.15, p = .043$) are observed, also confirmed by robust testing ($b = -1.58, HC3-SE = 0.72, t(227) = -2.19, p = .030$). In both analyses, this indicates that the knowledge effect is weaker in the control group (Group 0) than in the treatment group (Group 1). This suggests that the lower ranks (11-15) serve as a potential negative signal that triggers a more knowledge-based selection process. For participants in the treatment group, these specific ranks could potentially act as a 'negative anchor' (the last-placed) - a hypothesis that warrants further empirical investigation. While investment knowledge exerts a general main effect, this influence appears to be more pronounced in the treatment group than in the control group. Because the control group lacks this ranking signal entirely, the treatment's impact does not manifest as a uniform main effect, but instead emerges through the interaction, suggesting that expertise may intensify the reaction to a poor ranking. No significant interactions were found in the other buckets; instead, the results predominantly suggest additive main effects. Notably, for the "lesser-known" bucket on the extensive margin, there is a marginal group effect ($F(1, 240) = 3.68, p = .056$) and a positive knowledge effect ($F(1, 240) = 10.48, p = .001$), but no interaction between the two. Similarly, on the intensive margin for the "Top 1-5" bucket, no interaction occurs, although a marginal group effect ($F(1, 228) = 2.91, p = .089$) and a significant main effect of knowledge ($F(1, 228) = 5.80, p = .017$) are present.

In the quantity analysis (number of investments), the group effects also remain largely robust across all models; the inclusion of investment knowledge does not substantially alter the findings. Notably, in Models 2 and 3, investment knowledge emerges as a significant main effect in five out of six buckets (the exception being the 'unranked' bucket). At the same time, no significant interactions between group and knowledge are observed. This points toward additive relationships, meaning that in terms of the number of selected titles, quantity is systematically related to investment knowledge. Combined with the weighting results, this suggests that the ranking primarily influences the allocation structure across categories, whereas investment knowledge is more closely associated with the breadth of the selection (quantity).

Tab. 11: Tests for differences by group: weighting of selected brands incl. 0-Investments: Extensive margin;incl. covariate

Bucket weighting	Factor	Modell 1	Modell 2	Modell 3
Rank 1-5	Group	F = 2.273; p = .133	F = 2.265; p = .134	F = 2.273; p = .133
	Knowledge	–	F = 2.587; p = .109	F = 2.385; p = .124
	Group × Knowledge	–	–	F = 1.674; p = .197
Rank 6-10	Group	F = .640; p = .424	F = .642; p = .424	F = .639; p = .425
	Knowledge	–	F = .224; p = .637	F = .216; p = .643
	Group x Knowledge	–	–	F = .019; p = .890
Rank 11-15	Group	F = 1.397; p = .238	F = 1.397; p = .238	F = 1.413; p = .236
	Knowledge	–	F = 5.281; p = .022	F = 4.900; p = .028
	Group x Knowledge	–	–	F = 3.579; p = .060
unranked	Group	F = 4.212; p = .041	F = 4.244; p = .040	F = 4.234; p = .041
	Knowledge	–	1.526; p = .218	F = 1.434; p = .232
	Group x Knowledge	–	–	F = .498; p = .481
Top 10	Group	F = 4.579; p = .033	F = 4.565; p = .034	F = 4.574; p = .033
	Knowledge	–	F = 1.536; p = .216	F = 1.392; p = .239
	Group x Knowledge	–	–	F = 1.406; p = .237
lesser known	Group	F = 3.504; p = .062	F = 3.698; p = .056	F = 3.683; p = .056
	Knowledge	–	F = 10.544; p = .001	F = 10.479; p = .001
	Group x Knowledge	–	–	F = .000; p = .987

Tab. 12: Tests for differences by group: weighting of selected brands - Investments >0: Intensive Margin: incl. covariate

Bucket Weighting > 0	Factor	Modell 1	Modell 2	Modell 3
Rank 1-5	Group	F = 2.881; p = .091	F = 2.834; p = .094	F = 2.909; p = .089
	Knowledge	–	F = 6.019; p = .015	F = 5.799; p = .017
	Group × Knowledge	–	–	F = 1.411; p = .236
Rank 6-10	Group	F = 3.708; p = .056	F = 3.664; p = .057	F = 3.567; p = .060
	Knowledge	–	F = .222; p = .638	F = .225; p = .636
	Group x Knowledge	–	–	F = .117; p = .733
Rank 11-15	Group	F = .411; p = .522	F = .414; p = .521	F = .481; p = .489
	Knowledge	–	F = 3.261; p = .072	F = 3.038; p = .083
	Group x Knowledge	–	–	F = 4.150; p = .043
unranked	Group	F = .711; p = .401	F = .877; p = .351	F = .861; p = .355
	Knowledge	–	F = 1.805; p = .181	F = 1.796; p = .182
	Group x Knowledge	–	–	F = .028; p = .866
Top 10	Group	F = 5.317; p = .022	F = 5.246; p = .023	F = 5.253; p = .023
	Knowledge	–	F = 2.140; p = .145	F = 2.039; p = .155
	Group x Knowledge	–	–	F = .691; p = .407
lesser known	Group	F = 6.922; p = .010	F = 6.924; p = .010	F = 5.942; p = .016
	Knowledge	–	F = .063; p = .802	F = .037; p = .848
	Group x Knowledge	–	–	F = .082; p = .775

Tab. 13: Tests for differences by group: Quantity of selected brands: incl. covariate

Bucket Quantity	Factor	Modell 1	Modell 2	Modell 3
Rank 1-5	Group	F = .802; p = .371	F = .802; p = .371	F = .807; p = .370
	Knowledge	–	F = 7.898; p = .005	F = 8.392; p = .004
	Group × Knowledge	–	–	F = 2.631; p = p.106
Rank 6-10	Group	F = 1.878; p = .172	F = 1.892; p = .170	F = 1.893; p = .170
	Knowledge	–	F = 7.110; p = .008	F = 7.391; p = .007
	Group x Knowledge	–	–	F = 1.194; p = .276
Rank 11-15	Group	F = 8.004; p = .005	F = 8.563; p = .004	F = 8.528; p = .004
	Knowledge	–	F = 20.208; p < .001	F = 20.107; p = .001
	Group x Knowledge	–	–	F = .005; p = .943
unranked	Group	F = 7.526; p = .007	F = 7.490; p = .007	F = 7.531; p = .007
	Knowledge	–	F = .192; p = .662	F = .266; p = .607
	Group x Knowledge	–	–	F = 2.398; p = .123
Top 10	Group	F = 1.601; p = .207	F = 1.620; p = .204	F = 1.628; p = .203
	Knowledge	–	F = 9.203; p = .003	F = 9.682; p = .002
	Group x Knowledge	–	–	F = 2.226; p = .137
lesser known	Group	F = .108; p = .742	F = .103; p = .748	F = .103; p = .748
	Knowledge	–	F = 11.951; p = .001	F = 12.309; p = .001
	Group x Knowledge	–	–	F = 1.193; p = .276

5. Conclusion & Discussion

5.1 Summary of Results & Implications

This study examined how brand value rankings influence private investors' portfolio decisions, distinguishing between the extensive margin (whether to invest) and the intensive margin (how much to invest). The findings reveal a consistent, differentiated pattern across hypotheses.

H1 receives support: Rankings systematically shift capital allocation along the rank structure. Highly ranked brands benefit primarily on the intensive margin - when participants invest, they allocate significantly higher amounts (4 of the top 5 and 6 of the top 10 brands show significantly higher weightings), consistent with cue utilization (Olson & Jacoby, 1972; Tversky & Kahneman, 1974). Conversely, lower-ranked and unranked brands are less likely to be selected, primarily on the extensive margin: the treatment group systematically excludes these titles, as evidenced by significantly higher investment frequencies in the control group. Binary choice analysis reinforces this finding: Unranked brands and ranks 10-15 are selected more frequently when rankings are absent, indicating that rankings act as a binary filter that reduces investment probability for weak signals (Barber & Odean, 2008; Spence, 1973). This dual mechanism demonstrates that rankings function simultaneously as allocation anchors (intensive margin) and selection filters (extensive margin), a pattern that remains robust in aggregated bucket-level analysis (Tab. 7/8).

H2 is supported: Participants exposed to rankings construct more concentrated portfolios by holding fewer distinct companies. The treatment group holds significantly fewer positions in the lower-ranked (11-15) and unranked buckets, while the number of positions in top buckets does not significantly increase. This concentration effect demonstrates that rankings narrow portfolio breadth selectively, primarily affecting brands that send weaker or absent signals, consistent with behavioral portfolio theory, which predicts that investors focus on salient mental layers rather than pursuing broad diversification (Shefrin & Statman, 2000).

H3 receives tentative support on the intensive margin: For lesser-known but highly ranked brands, we observe higher allocations in the treatment group. Because these comparisons are based on small unknown-only subsamples (Table 6), we view the evidence as preliminary and interpret rankings as potential - rather than definitive - substitute signals for brand familiarity (Keller, 1993; Erdem & Swait, 2001) and as external cues when prior knowledge is limited (Rao & Monroe, 1988). However, bucket-level analysis (with higher case samples) confirms the pattern for the aggregated cluster of lesser-known brands (Tab. 8), demonstrating that

rankings can provide external orientation for unfamiliar brands - particularly when internal knowledge structures are absent - as long as these brands are positioned highly in the ranking.

Across all three hypotheses, bucket-level analyses (Tab. 7, 8, 9) confirm the robustness of these effects at an aggregated level, demonstrating that the observed patterns are not driven by individual brand characteristics but reflect systematic treatment effects along the ranking structure.

Regarding the role of investment knowledge, the analysis reveals additive rather than interactive relationships. While higher subjective investment knowledge is robustly associated with broader portfolio diversification across five of six analyzed buckets, it does not systematically attenuate the ranking's influence on allocation. The treatment effect on weighting operates predominantly independent of participants' knowledge level. This suggests that rankings primarily influence allocation structure across categories, whereas investment knowledge is more closely associated with portfolio breadth.

In summary, brand value rankings exert dual influence: They act as selection filters on the extensive margin - reducing the likelihood of investing in unranked/ lower-ranked brands - and as allocation anchors on the intensive margin - concentrating capital in top-ranked brands. These mechanisms operate largely independent of investor knowledge, underscoring the behavioral potency visible brand signals in structuring investment decisions.

These findings highlight the practical relevance of brand value rankings as a means of translating intangible brand strength into a comparable, visible metric. A top-tier ranking position can compensate for low brand awareness, while absence from rankings acts as a weak signal that may trigger exclusion. The findings lead to three implications: (1) Financial education should emphasize a reflective approach to rankings as behavioral cues, particularly since higher investor knowledge - while associated with greater portfolio breadth - does not systematically neutralize their influence. (2) For companies and investor relations, visibly communicated brand value serves as a guidance tool that demonstrably shapes investment decisions; rankings may thus function as strategic communication devices, especially for lesser-known brands seeking visibility. (3) Ranking providers and media bear responsibility for methodological transparency, as their publications structure investment behavior and may inadvertently reinforce allocation inequalities between visible and less visible brands (Dutordoir et al., 2015; Shafi et al., 2018).

5.2 Limitations and future research

Despite these findings, the study is subject to several limitations. First, it is based on an experimental setting with fictitious portfolio decisions in a simplified information environment; therefore, real financial consequences and the generalizability to complex market behavior can only be captured to a limited extent (Harrison & Rutström, 2008; Haghani et al., 2021). Second, while the observed effects are statistically significant and robust across analytical levels, they represent systematic realignments rather than radical portfolio restructuring. The ranking led to verifiable, nuanced shifts in allocation patterns, not to wholesale reallocation. Furthermore, the ranking stimulus was based on a selected and adapted subset of Brand Finance positions, which may limit the generalizability of the ranking effect to full real-world rankings. Third, the design only captures the impact of a single exposure and does not account for learning or feedback processes over time. Fourth, investor knowledge is measured through self-assessment rather than objective competence (Allgood & Walstad, 2016). Future research should integrate validated objective financial literacy measures - e.g. the three-item scale by Lusardi and Mitchell (2011, 2014, 2015) the 13-item by Fernandes et al. (2014), or the scale by van Rooij et al. (2011), which consists of 16 items that distinctively capture both basic knowledge and advanced financial concepts. Interestingly, the latter study by Rooij et al. (2011) found a very strong correlation between objective and subjective literacy, revealing that individuals' self-reported knowledge to some extent reflects their actual financial competence (p.458). Incorporating such measures would make it possible to test whether brand-ranking effects differ across investors with varying levels of factual financial knowledge, and thereby clarify whether brand-based decisions are primarily driven by knowledge gaps or whether they persist even among financially literate investors.

Further longitudinal studies could examine whether ranking effects persist, strengthen, or fade with repeated exposure and investor learning. In addition, analysing how rankings interact with other information signals - such as analyst recommendations, ESG scores, or social media sentiment - would provide a more realistic picture of decision-making in today's multi-signal investment landscape. Finally, exploring whether negative ranking changes (i.e., brands moving down in the ranking) trigger disproportionate sell-offs could shed light on the asymmetric impact of brand signals in capital markets.

Appendix

Tab. 14. Brand Awareness

	Not Known	Known
APPLE	1 (0,4%)	243 (99,6%)
AMAZON	1 (0,4%)	243 (99,6%)
ICBC	220 (90,2%)	24 (9,8)
VERIZON	180 (73,8%)	64 (26,2%)
MERCEDESSENZ	3 (1,2%)	241 (98,8%)
TENCENT	201 (82,4%)	43 (17,6%)
PINGAN	234 (95,9%)	10 (4,1%)
HOMEDEPOT	138 (56,6%)	106 (43,4%)
DISNEY	1 (0,4%)	243 (99,6%)
MCDONALDS	2 (0,8%)	242 (99,2%)
COCACOLA	3 (1,2%)	241 (98,8%)
NIKE	1 (0,4%)	243 (99,6%)
UPS	9 (3,7%)	235 (96,3%)
MASTERCARD	5 (2%)	239 (98%)
SAP	43 (17,6%)	201 (82,4%)
DOUGLAS	5 (2%)	239 (98%)
LIDL	1 (0,4%)	243 (99,6%)
SKODA	4 (1,6%)	240 (98,4%)
HARDROCKCAFE	14 (5,7%)	230 (94,3%)
CALVINKLEIN	4 (1,6%)	240 (98,4%)

Tab. 15: Example of randomized list of the twenty companies available for investment; visual identical for both groups

Coca-Cola	0 %
Disney	0 %
Hard Rock Cafe	0 %
Calvin Klein	0 %
Nike	0 %
Apple	0 %
ICBC	0 %
Mastercard	0 %
Tencent	0 %
McDonald's	0 %
Lidl	0 %
SAP	0 %
Amazon	0 %
UPS	0 %
Mercedes-Benz	0 %
Verizon	0 %
Douglas	0 %
Ping An	0 %
The Home Depot	0 %
ŠKODA	0 %
Sum	0 %

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