

American University Kyiv

A Capstone Project

EVALUATION OF MULTI-BRAND STRATEGY EFFECTIVENESS IN NICHE E-COMMERCE UNDER SPONSORED SEARCH AUCTIONS: EVIDENCE FROM CONTRIBUTION MARGIN ANALYSIS

ОЦІНКА ЕФЕКТИВНОСТІ МУЛЬТИБРЕНДОВОЇ СТРАТЕГІЇ В НІШЕВОМУ Е-COMMERCE В УМОВАХ АУКЦІОНІВ ПОШУКОВОЇ РЕКЛАМИ: ЕМПІРИЧНІ ДАНІ НА ОСНОВІ АНАЛІЗУ МАРЖИНАЛЬНОГО ДОХОДУ

by Dmytro Shukhrov

Presented in Partial Fulfillment of the Requirements
for the Degree

Master

APPROVED BY:
Olga Katerna, Ph.D., Faculty Mentor

2026

Abstract

Research Problem and Aim. The growth of digital advertising platforms has created new scaling opportunities for e-commerce companies beyond a single brand. Company X — a niche custom-printed wallpaper manufacturer operating exclusively online — sequentially launched a second (Brand 2) and third (Brand 3) brand in the same geographic markets to accelerate contribution margin growth. The decision was made intuitively, without empirical justification, and raised a key managerial question: would brands with overlapping catalogs but different price positioning cannibalize each other's demand? The study aims to retrospectively and empirically assess the financial effectiveness of Company X's multi-brand strategy, test whether the margin effect is additive or substitutive, and identify the mechanisms explaining the presence or absence of price cannibalization.

Research Questions and Hypotheses. The study is structured around four research questions. RQ1: what is the quantitative effect of transitioning from a single-brand to a multi-brand model on total contribution margin across three markets? RQ2: is margin growth attributable to reaching new audience segments or to compensating for exhausted advertising potential of the incumbent brand? RQ3: does the risk of price cannibalization materialize between co-owned brands with different positioning but partially overlapping catalogs? RQ4: how does geographic market size moderate the absolute and relative effect of the strategy? Two non-trivial hypotheses are tested: H1 — brands do not exhibit significant demand redistribution due to algorithmic audience segmentation and natural price-based segmentation; H2 — the multi-brand model generates an additive, not substitutive, increment in contribution margin.

Methodology. The study employs a quantitative, longitudinal, retrospective design of a natural quasi-experiment type. The unit of analysis is a country \times brand \times month observation. Company X's internal monthly financial data across three brands and three countries (Poland, Germany, Czech Republic) for the period February 2022 – March 2026 were used, yielding 135 valid observations. Contribution margin was converted from UAH to EUR at the official NBU exchange rate. Analytical methods: Welch t-test for between-phase comparisons, OLS and log-log regressions for advertising efficiency analysis, counterfactual projection for comparing single-brand and multi-brand scenarios, server-side cookie matching for measuring audience overlap. Analysis performed in Python (pandas, scipy.stats).

Key Results. Contribution margin grew in all three markets from Phase 1 (one brand) to Phase 3 (three brands): Poland +48.9% ($p < .001$), Germany +120.7% ($p < .001$), Czech Republic

+133.3% ($p < .001$). The counterfactual assessment for Poland shows that the multi-brand model outperformed the equivalent single-brand scenario by +8,861 EUR per month. For Czech Republic, the counterfactual revealed a short-term disadvantage in Phase 2 (-1,150 EUR/month) due to the incumbent brand's increasing marginal returns (slope = 2.57), though the overall Phase 1 to Phase 3 effect remains positive. No significant decline in Brand 1 margin was found after any launch (all $p > .05$). Maximum audience overlap across all brand pairs did not exceed 5.23% (Brand 3 and Brand 2, Poland); for pairs involving Brand 1 the maximum was 3.54%. Brand 2 significantly grew after Brand 3 launch in Germany ($p = .016$) and Czech Republic ($p = .013$), indicating positive portfolio complementarity.

Conclusions and Implications. H1 is not rejected: co-owned brands do not exhibit significant demand redistribution due to two mechanisms — algorithmic audience segmentation (different launch timing forms distinct seed audiences) and natural price-based segmentation (different positioning attracts buyers with different price sensitivity). H2 is confirmed: the multi-brand model generates an additive margin increment on top of the growing incumbent brand. An important nuance: strategy effectiveness depends on the maturity stage of the incumbent brand. In early-stage markets where the brand exhibits increasing marginal returns (slope > 1), launching a second brand may be premature in the short term. The study introduces the concept of brand maturity stage as a moderator of multi-brand strategy effectiveness and provides empirical evidence of algorithmic audience segmentation as a cannibalization-prevention mechanism — a contribution not documented in the current literature on digital advertising auctions and brand portfolio management. For Company X, it is recommended to use brand maturity indicators (advertising slope, YoY margin dynamics) as the trigger for launching a new brand instead of waiting for saturation, and to invest in Brand 2 content differentiation as structural long-term protection against potential future cannibalization.

Keywords: *multi-brand strategy, contribution margin, demand cannibalization, algorithmic audience segmentation, e-commerce, digital advertising auctions, brand portfolio, counterfactual analysis, price-based segmentation, brand maturity stage*

TABLE OF CONTENTS

Abstract.....	2
CHAPTER 1	6
INTRODUCTION	6
1.1 Research Background.....	6
1.2 Problem Statement	6
1.3 Research Aim	7
1.4 Research Questions	7
1.5 Scientific and Practical Significance.....	8
1.6 Methodology Overview	9
1.7 Research Limitations.....	9
CHAPTER 2	10
THEORETICAL FOUNDATIONS OF MULTI-BRAND STRATEGY IN DIGITAL ADVERTISING ENVIRONMENTS	10
2.1 Introduction.....	10
2.2 Theoretical Foundations.....	10
2.3 Review of Academic Research	12
2.4 Critical Analysis and Research Gap	14
2.5 Conceptual Framework and Link to Research Questions.....	16
2.6 Summary	18
CHAPTER 3	20
RESEARCH DESIGN AND METHODOLOGY	20
3.1 Research Design.....	20
3.2 Sample and Participants.....	20
3.3 Data Collection Instruments	21
3.4 Data Collection and Preparation Procedure.....	22
3.5 Ethical Considerations	22
3.6 Data Analysis Methods.....	22
3.7 Research Hypotheses	24
3.8 Chapter Summary	25
CHAPTER 4	26
EMPIRICAL RESULTS OF THE MULTI-BRAND STRATEGY ANALYSIS	26
4.1 Results for RQ1: Effect of Brand Count on Contribution Margin.....	26
4.2 Results for RQ2: Advertising Efficiency and Marginal Returns	29
4.2.1 <i>Did Brand 1 Reach Advertising Budget Saturation?</i>	29

4.2.2 <i>Mechanisms for Reaching New Audiences</i>	31
4.2.3 <i>Regression Analysis (Phase 1, Additional Evidence)</i>	32
4.3 Results for RQ3: Demand Cannibalization.....	34
4.3.1 <i>Financial Analysis — Brand 2 Launch</i>	34
4.3.2 <i>Financial Analysis — Brand 3 Launch</i>	35
4.3.3 <i>Audience Overlap Analysis</i>	36
4.4 Results for RQ4: Market Size and Strategy Effectiveness	37
4.5 Chapter Summary	38
CHAPTER 5	40
CONCLUSIONS	40
5.1 Answers to Research Questions.....	40
5.2 Theoretical Implications	41
5.3 Practical Recommendations.....	41
5.4 Research Limitations	42
5.5 Directions for Future Research.....	42
5.6 General Conclusion.....	43
REFERENCES	44

CHAPTER 1

INTRODUCTION

1.1 Research Background

As the digital economy expands, a growing share of commercial activity is moving into e-commerce environments. For most e-commerce companies, the primary customer acquisition channel is digital advertising — particularly paid search and targeted advertising tools that operate through algorithmic auction mechanisms. In such markets, competition occurs not only at the product or brand level, but also at the level of algorithmic access to consumer demand.

Company X sells a niche product — custom-printed designer wallpaper — through a network of country-specific websites. Low purchase frequency (on average once every few years) limits rapid scaling through a single brand.

To overcome these limitations, the company chose to sequentially launch multiple brands within the same market — based on the assumption that advertising platforms, when launched at different times, naturally find different audience segments.

1.2 Problem Statement

Company X operates three brands in the niche e-commerce wallpaper segment. Brand 1 is the oldest and most developed brand, operating since 2016 and serving as the sole brand in most markets for an extended period. Poland became the first and strongest market for Brand 1 in Europe, achieving the highest sales volumes and margins, and serving as the strategic benchmark for the company's decisions. At the start of the analysis horizon (February 2022), Poland remained the flagship market while other countries (Germany and Czech Republic) were at earlier stages of development.

After launching Brand 2, two managerial questions emerged. First — price cannibalization: Brand 2 offered identical designs at lower prices, creating a risk that buyers finding a product on Brand 1 would switch to Brand 2 — the company would earn lower margin while doubling advertising spend. Second — the mechanism of effect: does the multi-brand model generate new buyers or merely redistribute existing demand between brands?

With the addition of Brand 3 (even cheaper), the managerial dilemma deepened: has the multi-brand strategy justified itself financially, has the cannibalization risk materialized, and if not — through what mechanisms.

The key methodological challenge: margin growth alone does not prove strategy effectiveness — it is necessary to distinguish whether this results from new audiences or could have occurred without the multi-brand approach.

Table 1.1 describes the price positioning of the three brands.

Table 1.1. *Brand Characteristics of Company X*

Brand	Positioning	Price Segment	Content Strategy
Brand 1 (incumbent)	Premium	Above market	Over 20% exclusive designs not available at competitors
Brand 2 (second)	Mid-range	Below Brand 1	Primarily base catalog; exclusive content in development
Brand 3 (third)	Budget	Lowest of the three	Base catalog without specific content development

Source: developed by the author.

1.3 Research Aim

The aim of the study is to retrospectively and empirically assess the effectiveness of Company X's multi-brand strategy in terms of its impact on total contribution margin, to test the hypothesis of an additive (rather than substitutive) nature of this effect, and to identify the mechanisms that explain the presence or absence of price cannibalization between brands with different price positioning and partially overlapping product catalogs.

1.4 Research Questions

Four research questions were formulated:

RQ1: What is the quantitative effect of transitioning from a single-brand to a multi-brand model on total contribution margin of Company X across three European markets of different scale?

RQ2: Is contribution margin growth in the multi-brand model attributable to reaching new audience segments — or to compensating for the exhausted advertising potential of the incumbent brand?

RQ3: Does the risk of price cannibalization materialize between co-owned brands with different price positioning but partially overlapping product catalogs — and what mechanisms determine its absence or presence?

RQ4: How does geographic market size moderate the absolute and relative effect of the multi-brand strategy on contribution margin?

Table 1.2 shows the logical link between the research questions and the managerial problem.

Table 1.2. *Research Questions and Their Link to the Managerial Problem*

Research Question	Analysis Type	Link to Problem
RQ1: What is the quantitative effect of transitioning from a single-brand to a multi-brand model on total contribution margin across three markets?	Descriptive / statistical	Basic validation of the strategic decision
RQ2: Is contribution margin growth attributable to reaching new audience segments, or to compensating for exhausted advertising potential of the incumbent brand?	Explanatory / mechanistic	Reveals whether the effect is structural (new audiences) or situational (saturation)
RQ3: Does the risk of price cannibalization materialize between co-owned brands with different price positioning but partially overlapping catalogs?	Explanatory / conditional	Directly tests the managerial concern that drove the decision
RQ4: How does geographic market size moderate the absolute and relative effect of the multi-brand strategy?	Comparative / contextual	Determines conditions of applicability across markets of different size

Source: developed by the author.

1.5 Scientific and Practical Significance

Practical significance. The results are directly applicable to decisions regarding: (a) development or consolidation of the brand portfolio; (b) allocation of advertising budgets; (c) content differentiation strategy as a mechanism for preventing cannibalization.

Scientific significance. The study contributes to the theory of digital advertising auctions the mechanism of natural algorithmic audience segmentation as a factor preventing cannibalization between co-owned brands — a topic that current literature addresses only for independent channels. Additionally, the study empirically operationalizes the distinction between additive and substitutive effects of a multi-brand strategy.

1.6 Methodology Overview

The study is based on a quantitative retrospective design. The empirical foundation consists of Company X's internal monthly financial data across three brands and three countries (Poland, Germany, Czech Republic) for the period February 2022 – March 2026. The unit of analysis is a country × brand × month observation. Contribution margin is converted from UAH to EUR at the official NBU exchange rate.

Poland — Brand 1's oldest and largest market, providing the longest single-brand horizon. Germany — the second large market for comparison. Czech Republic — a small early-stage market for testing RQ4.

Main analytical methods: Welch t-tests for between-phase margin comparisons, OLS and log-log regressions for advertising trend analysis, counterfactual projection for comparing multi-brand and single-brand scenarios, audience overlap analysis via the company's proprietary server-side cookie matching system. A detailed description of the methodology is provided in Chapter 3.

1.7 Research Limitations

The study has several limitations:

- Single company and niche segment. Data come from one company in one product category. External validity to other industries requires separate verification.
- Three markets. Sufficient for comparing large and small markets, but insufficient for formal statistical conclusions about the moderating effect of market size.
- Confounders in Poland. The change in advertising budget in 2022–2023 coincided with the elimination of the call center and funnel restructuring, limiting causal interpretation for RQ2 in Poland.
- Retrospective design. The absence of randomized control precludes strictly causal conclusions — results are interpreted as descriptive and quasi-experimental.
- Short Phase 2 in Germany. 5 months between Brand 2 and Brand 3 launch in Germany limits the statistical power of the before/after analysis for this transition.
- Limited overlap horizon. Server-side cookie matching data are available only for the last 6 months of the study horizon. Dynamic overlap analysis over time is impossible due to the absence of a complete data archive.

CHAPTER 2

THEORETICAL FOUNDATIONS OF MULTI-BRAND STRATEGY IN DIGITAL ADVERTISING ENVIRONMENTS

2.1 Introduction

Digitalization has shifted a significant share of commercial interactions into online environments where algorithmic platforms mediate relationships between firms and consumers. Search advertising operates through auction mechanisms that allocate positions based on bids and quality scores (Edelman et al., 2007).

Outcomes depend on the behavior of all auction participants. Companies have begun employing multi-brand strategies — operating multiple brands in the same market — to expand reach (Yu, 2020; Yilmazel & Ozer, 2022), despite the risk of internal competition (Blake et al., 2015; Shriver & Bollinger, 2022).

The central question: is a multi-brand strategy additive (each brand reaches a new audience) or substitutive (brands compete for the same buyers)? The aim of this chapter is to synthesize the literature and build a theoretical foundation for the analysis.

2.2 Theoretical Foundations

The key theoretical perspective is auction theory. The GSP model by Edelman et al. (2007) explains how advertising platforms allocate slots among competing advertisers. Deng et al. (2024) showed that auction outcomes significantly depend on participant behavior and market conditions. Jeziorski & Segal (2015) established that search demand is finite — advertisers compete for a limited pool of consumer attention.

Critically important for this study is the development of algorithmic bidding research. Aggarwal et al. (2024) and Chen (2023) demonstrate that modern ML algorithms of advertising platforms not only optimize bids but also form audiences independently for each campaign. Kim & Pal (2023) confirm that quality scores and advertising strategies substantially affect auction outcomes under algorithmic optimization. This means that two co-owned brands, launched at different times, may receive algorithmically distinct initial audiences (seed audiences) even within the same market — a mechanism central to answering RQ3 of this study.

Lewis & Rao (2015) argue that measuring advertising effectiveness is challenging due to nonlinear causal relationships. Guenther et al. (2025) emphasize the need for evaluation through contribution margin — which is the methodological approach of this study.

Brand portfolio theory (Yu, 2020; Yilmazel & Ozer, 2022; Rashid et al., 2024) describes architectural decisions (branded house vs. house of brands) and their influence on consumer attitudes. However, it rarely examines the interaction of portfolios with algorithmic advertising environments.

The concept of demand cannibalization (Blake et al., 2015; Shriver & Bollinger, 2022) demonstrates that new marketing channels may redistribute existing demand. This defines the risk tested in RQ3: whether price cannibalization occurs between brands with different positioning but partially overlapping catalogs. The study analyzes whether algorithmic and price-based segmentation prevent this risk.

Table 2.1 summarizes the key theoretical concepts.

Table 2.1. *Key Theoretical Concepts*

Concept	Key Authors	Core Idea	Relevance
Generalized Second-Price (GSP) Auction	Edelman et al. (2007); Deng et al. (2024)	Search advertising allocated through auction based on bids and quality scores.	Explains competition mechanism for co-owned brands in the same auction.
Algorithmic Audience Segmentation	Aggarwal et al. (2024); Kim & Pal (2023); Chen (2023)	ML algorithms independently optimize audiences for each campaign launched at different times.	Explains natural audience segmentation between brands — central to RQ3.
Advertising Efficiency and ROI	Lewis & Rao (2015); Guenther et al. (2025)	Advertising investments may exhibit diminishing marginal returns; evaluated via contribution margin.	Foundation for RQ2: testing whether incumbent brand reached advertising saturation.
Brand Portfolio Strategy	Yu (2020); Yilmazel & Ozer (2022); Rashid et al. (2024)	Companies manage multiple brands to cover different segments or positions.	Theoretical foundation of multi-brand strategies; justifies studying additive effect in RQ1 and RQ2.
Demand Cannibalization	Blake et al. (2015); Shriver & Bollinger (2022)	New channels or products may redistribute existing demand rather than generate new demand.	Defines the cannibalization risk tested in RQ3.
Market Size and E-Commerce	Mueller & Swoboda (2025); Meyer et al. (2024)	Market size and competitive intensity affect strategy performance.	Justifies the moderating effect analysis for RQ4.

Source: developed by the author.

2.3 Review of Academic Research

A substantial body of research has examined the functioning of digital advertising markets and related strategic questions. The auction dynamics strand (Kim & Pal, 2023; Chen, 2023; Aggarwal et al., 2024) shows that search advertising outcomes are determined not only by bid levels but also by advertiser quality and algorithmic interactions. Critically, ML algorithms of modern platforms independently form audiences for each campaign — key to understanding natural audience segmentation between brands.

Research on advertising investment effectiveness (Lewis & Rao, 2015; Almestarihi et al., 2024; Sharabati et al., 2024) shows that advertising's impact on profitability is difficult to measure and depends on organizational capabilities. Jeziorski & Segal (2015) establish a fundamental constraint: search demand is finite, so multiple brands in the same market compete for the same attention pool.

Brand portfolio research (Rashid et al., 2024; Teng et al., 2025; Platzek et al., 2025; Kumar et al., 2026) has evolved in response to digital transformation. It shows that architectural decisions affect consumer perceptions and portfolios can serve different strategic objectives. However, these works rarely examine the specific situation where multiple co-owned brands participate in the same algorithmic auction.

Cannibalization research (Chen et al., 2025; Xu, 2025; Zhu et al., 2025) analyzes how pricing strategies and platform infrastructure changes affect demand distribution across channels. Blake et al. (2015) demonstrate that paid advertising sometimes captures organic demand, while Shriver & Bollinger (2022) show that new channels redistribute rather than expand demand. These findings justify the expected cannibalization risk tested by RQ3.

Research on competitive dynamics and market size (Mueller & Swoboda, 2025; Meyer et al., 2024; Yan & Yuan, 2025; OECD, 2021) shows that market size and competition levels affect marketing strategy performance. Higher competition reduces the marginal effectiveness of marketing expenditure (Yan & Yuan, 2025), and competition for limited consumer attention is a defining feature of digital platforms (Meyer et al., 2024).

Table 2.2 summarizes the key academic studies.

Table 2.2. Summary Review of Key Literature

Authors	Domain	Method	Key Findings
Edelman et al. (2007)	Search Auctions	Theoretical model	GSP model for allocating ad slots.
Deng et al. (2024)	GSP Efficiency	Economic modeling	Results depend on participant behavior.
Chen (2023)	Dynamic Bidding	ML modeling	Advertisers adapt strategies in repeated auctions.
Kim & Pal (2023)	Sponsored Search	Econometrics	Ad quality significantly affects auction outcomes.
Aggarwal et al. (2024)	Automated Bidding	Literature review	ML bidding forms independent audiences for each campaign.
Jeziorski & Segal (2015)	Search Demand	Empirical	Search demand is finite; advertisers compete for the same attention.
Lewis & Rao (2015)	Ad Efficiency	Field experiment	Advertising effect is hard to measure; often smaller than expected.
Guenther et al. (2025)	Advertising & Profit	Marketing analytics	Efficiency should be evaluated via contribution margin.
Almestarihi et al. (2024)	Digital Ad ROI	Empirical	Advertising investments affect business profitability.
Sharabati et al. (2024)	Digital Marketing	Empirical	Marketing effectiveness depends on organizational capabilities.
OECD (2021)	Digital Ad Markets	Policy analysis	Markets are highly concentrated and platform-dependent.
Yu (2020)	Brand Architecture	Conceptual model	Branded house vs. house of brands framework.
Yilmazel & Ozer (2022)	Brand Portfolios	Consumer research	Portfolio structure affects consumer perception.
Rashid et al. (2024)	Brand Architecture	Conceptual framework	Architecture decisions affect brand positioning.
Teng et al. (2025)	Branding & Innovation	Empirical	Branding strategies affect brand equity.

Kumar et al. (2026)	Strategic Branding	Conceptual framework	When and how branding creates value.
Platzek et al. (2025)	Portfolio Transformation	Organizational	Brand portfolios support strategic transformations.
Blake et al. (2015)	Paid Search	Field experiment	Paid search can capture organic demand.
Shriver & Bollinger (2022)	Channel Cannibalization	Structural modeling	New channels redistribute rather than expand demand.
Chen et al. (2025)	Price Cannibalization	Analytical model	Pricing strategies can generate cannibalization.
Xu (2025)	Cannibalization Detection	Data clustering	Cannibalization effects detected through price and demand.
Zhu et al. (2025)	Platform Competition	Empirical	Platform strategies can combine trust and cannibalization.
Mueller & Swoboda (2025)	Market Size & E-Commerce	International	Market size affects e-commerce performance.
Meyer et al. (2024)	Competition for Attention	Strategic management	Digital markets involve competition for attention.
Yan & Yuan (2025)	Competition & Marketing	Economic analysis	Higher competition reduces marginal effectiveness of marketing.

Source: developed by the author.

2.4 Critical Analysis and Research Gap

Despite a substantial body of research, important gaps remain in the literature.

First, most advertising auction research treats advertisers as independent participants (Edelman et al., 2007; Deng et al., 2024). In practice, a single firm may participate in the same auction through multiple brands with different positioning — this type of internal competitive interaction is practically unstudied.

Second, advertising effectiveness research focuses predominantly on revenue or traffic. Few studies distinguish whether performance growth results from reaching new audience segments

or compensating for the exhausted potential of a single brand (Lewis & Rao, 2015; Guenther et al., 2025).

Third, brand portfolio research analyzes multi-brand strategies predominantly through the lens of segmentation or positioning (Yu, 2020; Yilmazel & Ozer, 2022), rarely examining the interaction of these strategies with algorithmic advertising auctions.

Fourth, cannibalization research examines predominantly the interaction between independent channels (Blake et al., 2015; Shriver & Bollinger, 2022). Internal price cannibalization between co-owned brands with different price positioning but partially overlapping catalogs remains practically unstudied.

Fifth — and this is the central gap for this study — none of the reviewed research examines the mechanism of natural audience segmentation between co-owned brands through ML algorithms of advertising platforms. The question remains open: do Google and Meta algorithms provide independent audience optimization for different brands launched at different times, and can this algorithmic segmentation together with price differentiation explain the absence of significant demand redistribution even between brands with partially overlapping catalogs?

Finally, the role of market size in moderating the additive or substitutive nature of multi-brand strategies remains insufficiently studied. Although Mueller & Swoboda (2025) point to the influence of market size on performance, few studies directly analyze how market size moderates this effect in algorithmic advertising auctions.

Table 2.3 shows the identified research gaps.

Table 2.3. *Identification of Research Gaps*

Domain	Existing Findings	Limitations	Gap
Digital Advertising Auctions	GSP allocates traffic among independent advertisers.	Advertisers are treated as independent.	Multiple co-owned brands in the same auction have barely been studied.
Advertising Efficiency	Advertising may exhibit diminishing marginal returns.	Focus on revenue rather than contribution margin.	Lacking assessment of whether margin growth stems from new audiences or exhausted potential.
Brand Portfolio Strategies	Multi-brand helps segment the market.	Most studies based on traditional markets.	Limited evidence in algorithmic advertising environments.

Demand Cannibalization	New channels may redistribute demand.	Focus on independent channels or products.	Internal price cannibalization between co-owned brands with partially overlapping catalogs is barely studied.
Algorithmic Audience Segmentation	ML algorithms optimize audiences for each campaign.	Natural segmentation mechanism between co-owned brands has not been studied.	Unknown whether algorithms provide independent segmentation for brands with different price positioning and overlapping catalogs.
Market Context	Market size affects performance.	Few studies link market size to multi-brand strategy effectiveness in digital.	Unknown how market size moderates the effect of multi-brand strategies in digital auctions.

Source: developed by the author.

Overall, Table 2.3 demonstrates that although prior studies have examined auction mechanisms, advertising efficiency, brand portfolios, and cannibalization, they have rarely been integrated into a single analytical framework. In particular, the interaction between co-owned brands in the same algorithmic auction, the possibility of natural audience segmentation, and the moderating role of market size remain underexplored. Therefore, the present study addresses a clear research gap by empirically testing whether a multi-brand strategy in niche e-commerce generates an additive or substitutive effect on contribution margin.

2.5 Conceptual Framework and Link to Research Questions

Based on the reviewed literature and identified gaps, a conceptual research framework is proposed. The framework reflects two competing mechanisms that determine the nature of the multi-brand effect.

Substitutive mechanism (expected risk): brands compete for the same buyers, drive up each other's CPC, redistribute existing demand (Blake et al., 2015; Jeziorski & Segal, 2015). The risk of price cannibalization is particularly acute when brands offer identical or similar products at different prices.

Additive mechanism (examined in RQ2 and RQ3): advertising platforms, when launching new campaigns at different times, naturally form distinct seed audiences for each brand (Aggarwal et al., 2024; Kim & Pal, 2023), and price differentiation structurally separates buyers with

different price sensitivity. *It should be noted that the mechanism of algorithmic audience segmentation is a theoretical rationale, not a directly tested causal relationship — direct testing through platform data remains outside the scope of this study.*

Market size is a moderating variable that determines the absolute and relative scale of the effect (Mueller & Swoboda, 2025). Figure 2.1 illustrates this conceptual framework.

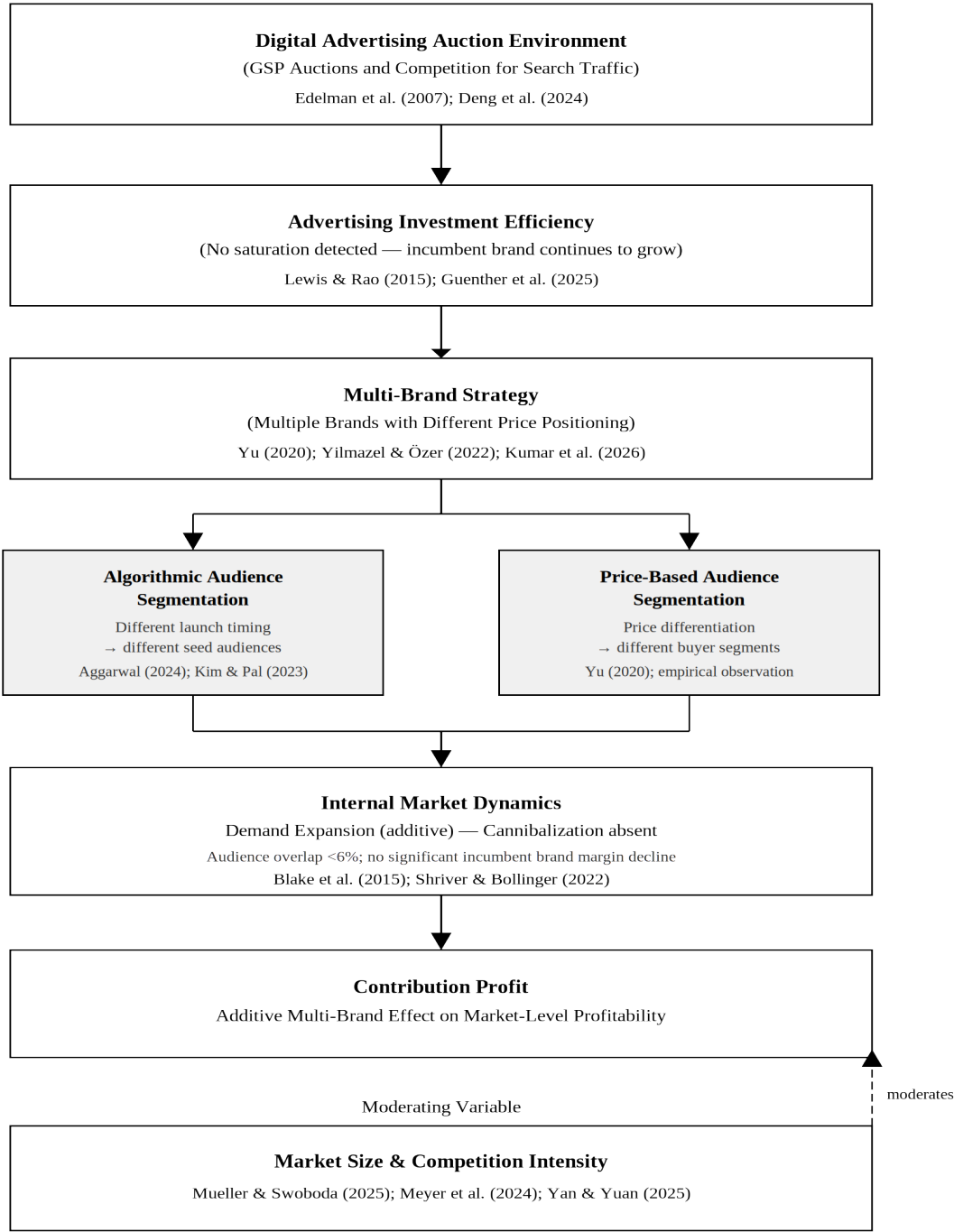


Figure 2.1. Conceptual Research Framework

Source: developed by the author.

Overall, Figure 2.1 demonstrates that the effect of a multi-brand strategy may follow either a substitutive or an additive logic, depending on the interaction between auction dynamics, audience segmentation, and market context. This conceptual framework therefore serves as the analytical bridge between the literature review and the empirical investigation conducted in the following chapters.

Table 2.4 links the reviewed literature to the research question formulations.

Table 2.4. Literature Foundations of Research Questions

Research Question	Key Literature	Concept
RQ1: What is the quantitative effect of the transition from single-brand to multi-brand model on contribution margin across three markets?	Yu (2020); Yilmazel & Ozer (2022); Rashid et al. (2024); Teng et al. (2025); Kumar et al. (2026)	Brand portfolio strategy; multi-brand positioning; additive vs. substitutive effect
RQ2: Is contribution margin growth attributable to new audience segments or to compensation for exhausted advertising potential?	Lewis & Rao (2015); Guenther et al. (2025); Aggarwal et al. (2024); Kim & Pal (2023); Chen (2023)	Advertising efficiency; algorithmic audience optimization; additive effect mechanism
RQ3: Does the risk of price cannibalization materialize between co-owned brands with different positioning and partially overlapping catalogs?	Blake et al. (2015); Shriver & Bollinger (2022); Chen et al. (2025); Xu (2025); Zhu et al. (2025)	Demand cannibalization; algorithmic and price-based segmentation
RQ4: How does geographic market size moderate the absolute and relative effect of the multi-brand strategy?	Mueller & Swoboda (2025); Meyer et al. (2024); Yan & Yuan (2025); OECD (2021)	Market size, competitive intensity, platform markets

Source: developed by the author.

2.6 Summary

The literature review demonstrates that research on digital advertising auctions, brand portfolio strategies, and demand cannibalization has largely developed as separate streams. Existing

works highlight the importance of auction mechanisms, potential risks of internal channel competition, and the influence of market size on strategy performance.

However, a critical gap exists: there are no integrated empirical studies evaluating whether a multi-brand strategy is additive or substitutive in algorithmic advertising environments — especially when brands have different price positioning but partially overlapping catalogs. The mechanism of algorithmic audience segmentation as a factor that, together with price differentiation, may prevent price cannibalization between co-owned brands is an open empirical question. This is precisely what this study addresses. The next chapter describes the methodology of the empirical analysis.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

3.1 Research Design

The study is based on a quantitative, longitudinal, and retrospective design. The quantitative nature is driven by the use of numerical financial and operational data with statistical methods. The longitudinal character reflects the coverage of the February 2022 – March 2026 horizon. The retrospective nature means that strategic decisions had already been made and the analysis is based on archival data.

The study is closest to a natural quasi-experiment: brand launch timing was determined by strategic decisions rather than randomization, creating a treatment–control structure. The unit of analysis is a country × brand × month observation.

3.2 Sample and Participants

The target population is all Company X markets with at least one active e-commerce brand. Purposive sampling: three countries meeting the criteria (≥ 12 months of Brand 1 as the sole active brand, complete financial records, available NBU exchange rate). 135 brand × month observations.

Table 3.1 — sample characteristics.

Table 3.1. *Sample Characteristics by Country*

Country	Brand 1 Launch	Brand 2 Launch	Brand 3 Launch	Market Size	Population	Total obs.
Poland	Feb 2022	Nov 2023	Sep 2024	Large	38M	50
Germany	Feb 2022	Mar 2024	Aug 2024	Large	84M	50
Czech Republic	May 2023	Jun 2024	Mar 2025	Small	11M	35
Total	—	—	—	—	—	135

Source: developed by the author.

Poland and Germany are large markets (38 and 84 million). Czech Republic is a small market (11 million).

Brand price positioning. Brand 1 is a premium brand with over 20% exclusive content (as of 2025). Brand 2 offers lower prices and a base catalog. Brand 3 is the cheapest. This price differentiation is a structural factor in natural audience segmentation: buyers with different price sensitivity gravitate toward different brands regardless of the algorithm. The lower price per m² for Brand 2 and Brand 3 implies lower margin per unit, which constrains the advertising budget without sacrificing profitability.

3.3 Data Collection Instruments

The study relies entirely on secondary data:

- Internal financial system. Monthly CSV files: advertising expenses (EUR), revenue excl. VAT (EUR), gross contribution (UAH), m².
- NBU exchange rates. Monthly EUR/UAH end-of-month rates. Range: 31.1–51.0 UAH/EUR.
- Seasonality indices. Country-level monthly indices from internal order data. Normalized to mean = 1.0.
- Server-side cookie matching system. Upon the first visit to any company website, the browser received a unique cookie via a separate server. Upon a subsequent visit to another brand site, the server detected a match and recorded the overlap. More reliable than GA4 cross-domain tracking.
- Eurostat. Population data for market classification.

Table 3.2 — variable operationalization.

Table 3.2. *Operationalization of Variables and Data Sources*

Variable	Type	Operationalization	Source
Contribution margin (EUR/month)	Dependent	Revenue minus costs; converted at the NBU exchange rate	Internal financial system
Number of active brands	Independent (treatment)	Number of brands with expenses > 0 in the month (1, 2, 3)	Internal operational reporting

Advertising expenses (EUR)	Independent (RQ2)	Total paid advertising expenses per brand per month	Internal financial system
Seasonally adjusted margin	Derived (RQ2)	Margin / country monthly seasonality index	Calculated from internal data
Brand launch event	Treatment indicator	Binary: 0 before launch; 1 from launch month	From advertising records
Audience overlap (%)	Auxiliary (RQ3)	Share of shared users between brands	Server-side cookie matching
Market size	Moderator (RQ4)	Large >20M / small <15M (Eurostat)	Eurostat

Source: developed by the author.

3.4 Data Collection and Preparation Procedure

Seven steps: (1) CSV extraction; (2) UAH→EUR conversion at NBU rates; (3) launch date identification (first month with ads > 0; test months < €100 excluded); (4) phase assignment (Phase 1: Brand 1 only; Phase 2: +Brand 2; Phase 3: +Brand 3); (5) seasonal margin adjustment for RQ2; (6) overlap data extraction from cookie system; (7) validation (EUR cross-validation via implicit rate, anomaly checks). The full pipeline was implemented in Python (pandas, scipy.stats, numpy).

3.5 Ethical Considerations

Anonymization (Company X), commercial confidentiality (aggregated data format), no personal data, exclusively academic use, conflict of interest disclosure (the researcher is an employee of the company).

3.6 Data Analysis Methods

Table 3.3 — summary of analytical methods.

Table 3.3. *Analysis Methods by Research Question*

RQ	Method	Description	Output
RQ1	Between-phase comparison + Welch t-test	Monthly country margin across Phases 1, 2, 3.	Mean margin, $\Delta\%$, t-statistic, p

RQ1	Counterfactual Projection (Poland)	Phase 1 regression coefficient → single-brand scenario.	Projected vs actual margin
RQ2	Brand 1 Trend Analysis	Linear regression of Brand 1 margin and advertising over time.	Slope, R ² , p
RQ2	OLS Linear Regression (Phase 1)	Margin ~ advertising. Tests sub-proportional returns.	slope, R ² , p
RQ2	Log-log Regression	$\beta < 1$ → decreasing; $\beta > 1$ → increasing marginal returns.	β , R ² , p
RQ3	Before/after + Welch t-test	Symmetric windows around each launch.	Mean before/after, $\Delta\%$, p
RQ3	Audience Overlap	Server-side cookie matching: share of shared users.	Overlap %, unique users
RQ4	Cross-Market Comparison	Same methodology applied to each market.	Absolute and relative effects

Source: developed by the author.

RQ1: between-phase comparison + Welch t-test ($\alpha = .05$) + counterfactual projection for Poland.

RQ2: Brand 1 trend analysis over the full horizon (linear regression of margin and advertising over time) to test whether saturation has been reached. Additionally — Phase 1 regressions (linear, log-log, quadratic, Spearman) as descriptive evidence. Key limitation for Poland: the budget decline in 2022–2023 coincided with call center elimination and conversion funnel restructuring — causal attribution is impossible.

RQ3: before/after comparison with symmetric windows (10 months PL/CZ, 5 months DE). Welch t-test for Brand 1 margin. Spearman correlation between brands. Overlap via server-side cookie matching.

RQ4: same RQ1/RQ3 methodology applied independently to each market. Descriptive cross-market comparison (n = 3; formal moderation regression is not applied).

3.7 Research Hypotheses

Based on the theoretical framework of Chapter 2 and the research questions of Chapter 1, two hypotheses were formulated. Unlike an approach where each RQ receives its own hypothesis, the hypotheses in this study are formulated around the key non-trivial questions — the mechanism and character of the effect — rather than around obvious empirical tests. Since the study is retrospective, the hypotheses are formulated based on theoretical expectations and prior managerial observations, consistent with a confirmatory approach in applied business research (Yin, 2018).

Table 3.4 — research hypotheses.

Table 3.4. Research Hypotheses

No.	Hypothesis
H1	Co-owned brands with different price positioning and partially overlapping product catalogs, operating in the same search advertising auction, do not exhibit significant demand redistribution between each other — due to algorithmic audience segmentation by advertising platforms (different launch timing → different seed audiences) and natural price-based segmentation of buyers with different price sensitivity. Falsifier: data could show a statistically significant decline in Brand 1 margin after new brand launches and/or overlap > 15%.
H2	Under conditions of algorithmic and price-based audience segmentation, the multi-brand model generates an additive, not substitutive, increment in contribution margin: new brands increase total margin on top of the growing incumbent brand, not at the expense of redistributing its demand or advertising budget. Falsifier: data could show that the combined margin of the multi-brand model does not exceed the counterfactual single-brand scenario, or that Brand 1 margin declines after new brand launches.

Source: developed by the author.

H1 is non-trivial because the standard logic of advertising auctions assumes that two co-owned brands in the same market will compete for the same buyers, drive up each other's CPC, and redistribute existing demand (Blake et al., 2015; Jeziorski & Segal, 2015). The hypothesis asserts the opposite and proposes two specific mechanisms: algorithmic segmentation via different campaign launch timing and price-based segmentation via different brand positioning.

H2 is non-trivial because prevailing brand portfolio theory allows for a trade-off between brands — when resources and management attention flow from the incumbent brand to new ones. Hypothesis H2 asserts the additive nature of the effect: Brand 1 continues to grow in parallel with new brands, and the multi-brand model outperforms the equivalent single-brand scenario. This is tested through counterfactual assessment.

Both hypotheses together answer the central research question: is a multi-brand strategy in an algorithmic search auction additive or substitutive?

3.8 Chapter Summary

This chapter presented: a quantitative retrospective quasi-experimental design; purposive sampling of three markets (135 observations); five data sources including a proprietary server-side cookie matching system; a seven-step data preparation procedure; Welch t-tests + regressions + trend analysis as the analytical toolkit; two non-trivial falsifiable hypotheses H1 and H2 that together address the question of additive vs. substitutive multi-brand effect.

Overlap data limitation. Server-side cookie matching data are available only for the last 6 months of the study horizon, not for the full period. Dynamic analysis of overlap over time is impossible due to the absence of a complete data archive.

The next chapter presents the empirical results.

CHAPTER 4

EMPIRICAL RESULTS OF THE MULTI-BRAND STRATEGY ANALYSIS

4.1 Results for RQ1: Effect of Brand Count on Contribution Margin

To answer RQ1, monthly country-level contribution margin was compared across three phases. Table 4.1 presents descriptive statistics; Table 4.2 presents Welch t-test results.

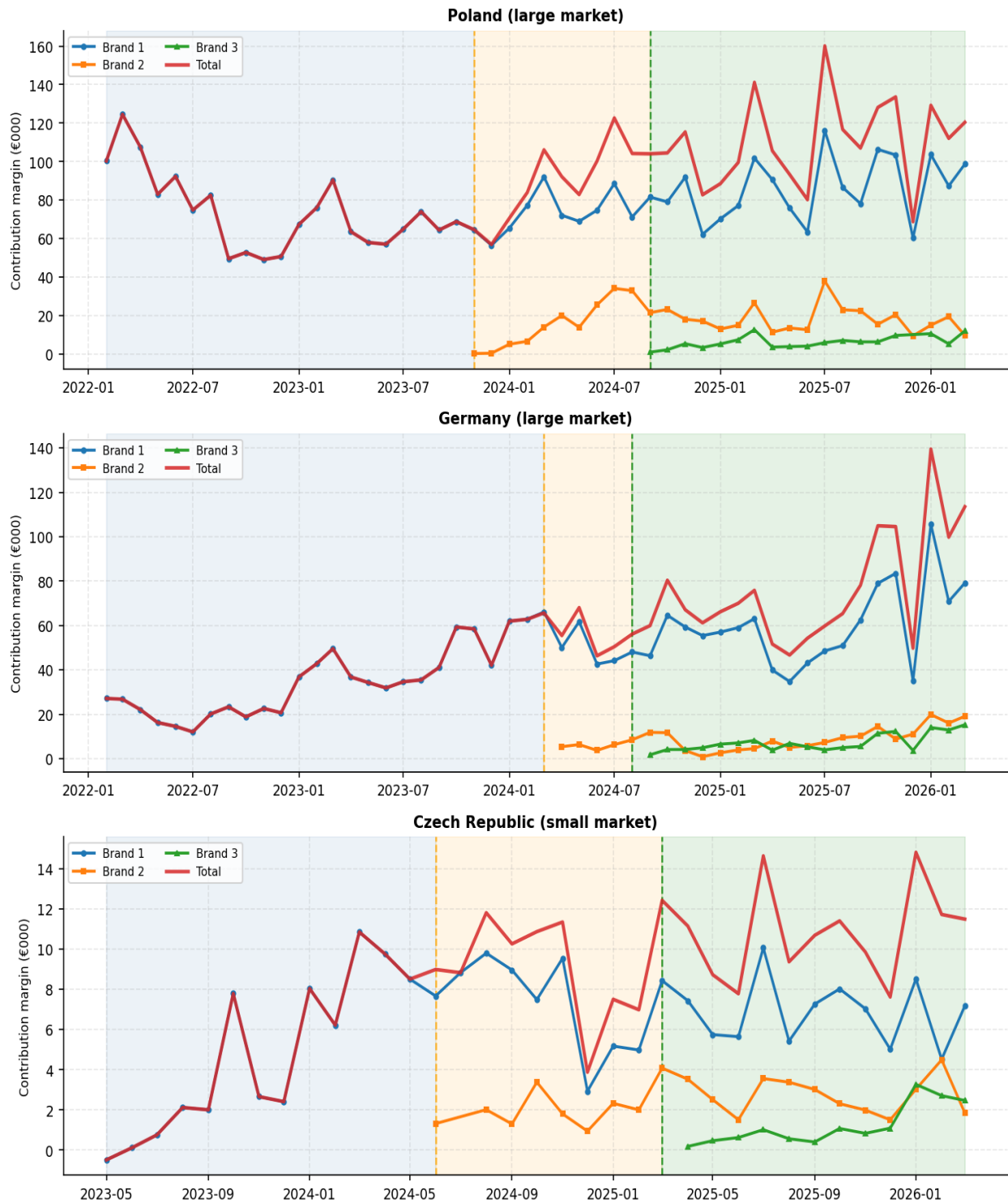
As shown in Table 4.1, margin grew in all three markets: Poland +48.9%, Germany +120.7%, Czech Republic +133.3% (Phase 1 → Phase 3). Advertising efficiency (margin/€ ads) changed differently: in Poland it declined in Phase 3 (1.75x → 2.19x → 1.65x); in Germany it also declined (2.82x → 1.75x) with the growth of Brand 3's budget; while in Czech Republic it increased (1.20x → 2.36x) — consistent with increasing marginal returns in an early-stage market.

Table 4.1. *Descriptive Statistics of Contribution Margin by Phase and Country*

Metric	PL Ph1	PL Ph2	PL Ph3	DE Ph1	DE Ph3	CZ Ph1	CZ Ph3
n (months)	21	10	19	25	20	13	13
Mean margin/month (€)	73,898	88,432	110,062	34,087	75,223	4,675	10,905
Std. deviation (€)	19,813	19,531	21,998	14,921	24,230	2,822	3,614
Mean revenue/month (€)	152,735	163,369	220,779	65,085	154,757	13,316	28,082
Mean advertising/month (€)	45,385	40,136	67,918	12,263	43,305	3,034	5,107
Margin per € advertising	1.75x	2.19x	1.65x	2.82x	1.75x	1.20x	2.36x

Source: developed by the author.

Figure 4.1 shows monthly margin dynamics. Figure 4.2 — phase comparison.



Note. Shading: Phase 1 (blue), Phase 2 (orange), Phase 3 (green). Dashed lines — launch dates.

Figure 4.1. Monthly Country-Level Contribution Margin by Phase

Source: developed by the author.

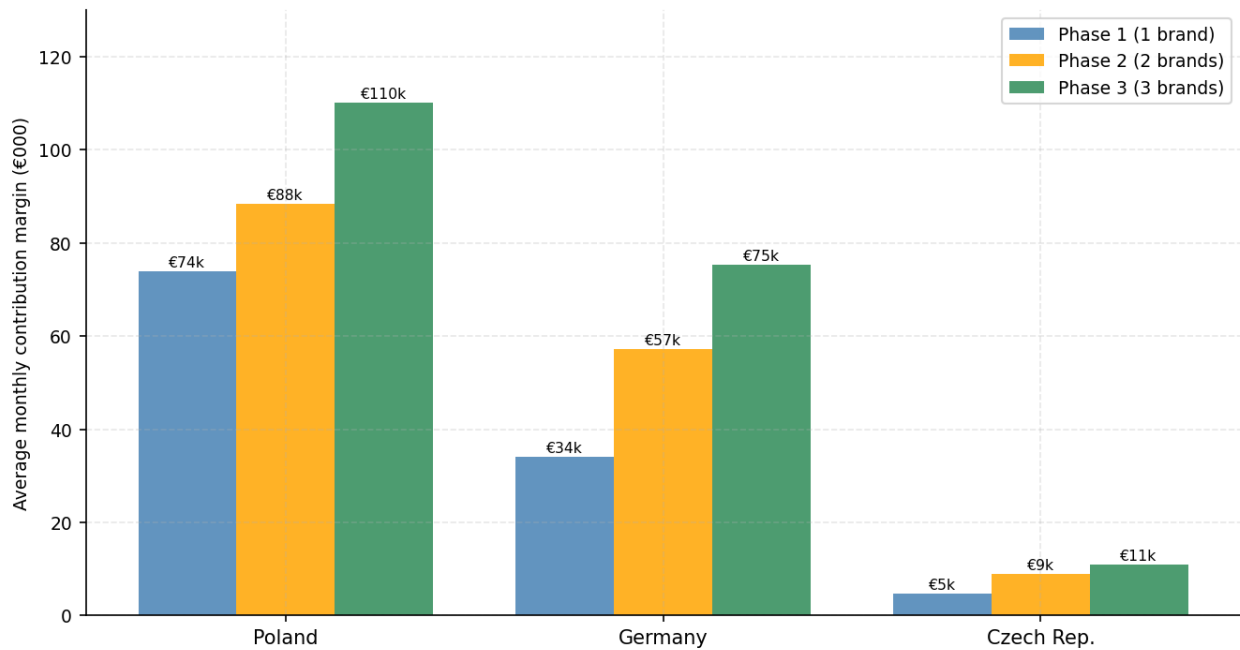


Figure 4.2. Average Monthly Contribution Margin by Phase and Country

Source: developed by the author.

Counterfactual Assessment (Poland). The Phase 1 linear regression (n = 21 months, February 2022 – October 2023) yielded slope = 0.648. Brand 2's mean monthly advertising budget in Phase 2 was €8,758/month. Had these funds been invested in Brand 1: $€73,898 + €8,758 \times 0.648 = \sim€79,573$ /month (projected single-brand scenario). Actual combined margin in Phase 2 — €88,432/month. Multi-brand advantage: +€8,861/month.

Interpretation caveats. slope = 0.648 is averaged over 21 months spanning two qualitatively different sub-periods: 2022 (budget €40–65K, call center, old funnel) and 2023 (budget €25–37K, restructured funnel). $R^2 = 0.242$ means the regression explains only 24% of margin variation. Given these limitations, +€8,861/month is an indicative lower bound — the actual effect may be larger.

Counterfactual Assessment (Czech Republic). Phase 1 regression: slope = 2.570, $R^2 = 0.813$, $p < .001$ (n = 13 months). Brand 2's mean budget in Phase 2 was €2,109/month. Had these funds been invested in Brand 1: $€4,675 + €2,109 \times 2.570 = \sim€10,095$ /month. Actual combined Phase 2 margin — €8,945/month. Difference: –€1,150/month in favor of the single-brand scenario.

Interpretation. Brand 1 in Czech Republic was in a phase of increasing marginal returns (slope = 2.57 > 1): each €1 of advertising budget generated €2.57 in margin. Brand 2 in its first months showed weak efficiency (0.79x) and even had a negative month (July 2024: –€3). In early-stage

markets, launching a second brand may be premature from a short-term margin perspective. The overall Phase 1→3 effect remains positive: +133.3% ($p < .001$).

Counterfactual Assessment (Germany) — Not Conducted. The Phase 1 regression does not reach statistical significance ($p = .082$). The advertising budget in Phase 1 varied over too narrow a range (€9–18K/month). $R^2 = 0.126$. The RQ1 analysis for Germany relies exclusively on between-phase comparison and the Welch t-test.

Table 4.2. *Welch t-Test Results for Between-Phase Comparisons*

Comparison	Country	t-statistic	p-value	n1 / n2	Result
Phase 1 vs Phase 2	Poland	-1.846	.082	21 / 10	Not significant
Phase 1 vs Phase 3	Poland	-5.303	<.001	21 / 19	Significant □
Phase 2 vs Phase 3	Poland	-2.599	.017	10 / 19	Significant □
Phase 1 vs Phase 2	Germany	-4.438	.002	25 / 5	Significant □
Phase 1 vs Phase 3	Germany	-6.490	<.001	25 / 20	Significant □
Phase 1 vs Phase 2	Czech Republic	-3.086	.006	13 / 9	Significant □
Phase 1 vs Phase 3	Czech Republic	-4.926	<.001	13 / 13	Significant □

Source: developed by the author.

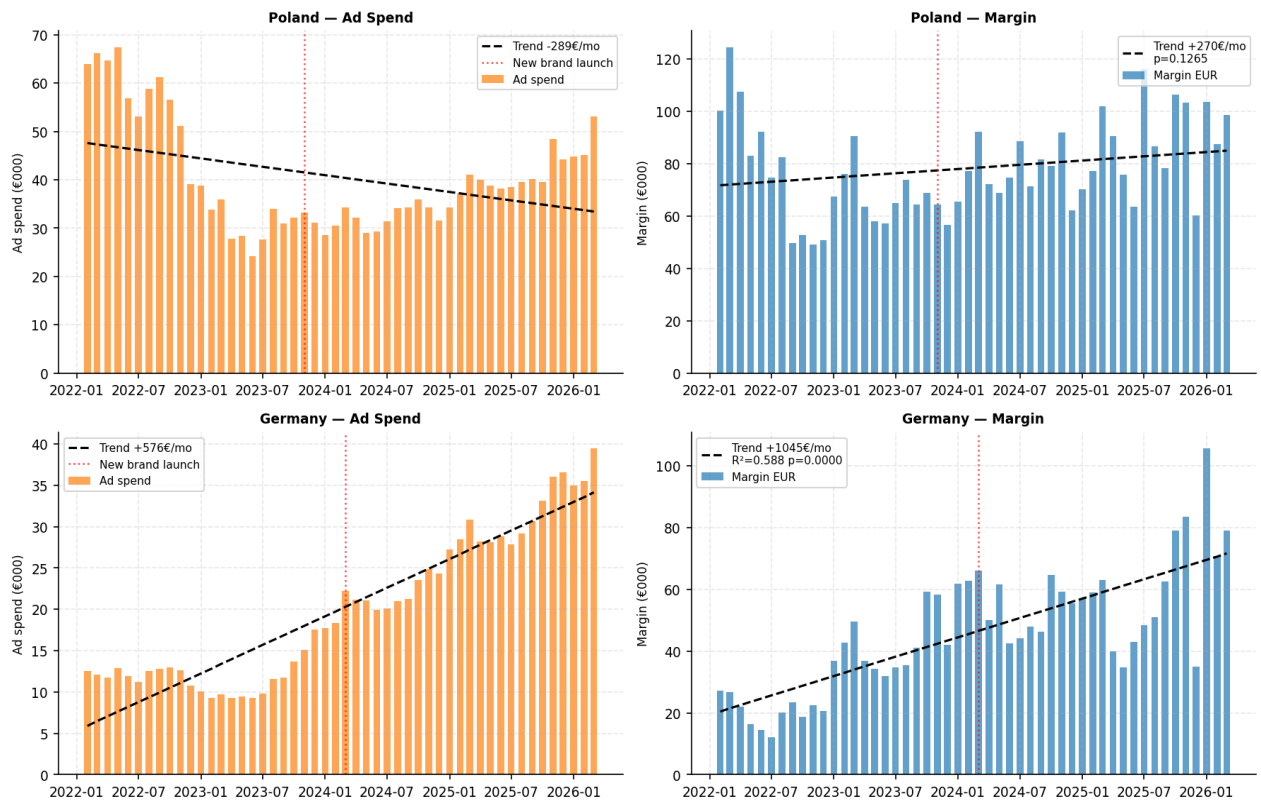
Phase 1 vs Phase 3 is significant at $p < .001$ in all countries. Phase 1 vs Phase 2 is not significant for Poland ($p = .082$, $n = 10$), but is significant for Germany ($p = .002$) and Czech Republic ($p = .006$).

4.2 Results for RQ2: Advertising Efficiency and Marginal Returns

4.2.1 Did Brand 1 Reach Advertising Budget Saturation?

The key question of RQ2 — whether Brand 1 exhausted its advertising potential before the launch of new brands. A Brand 1 trend analysis was conducted over the full time horizon.

Figure 4.3 shows Brand 1 advertising expenditure and contribution margin dynamics for Poland and Germany. Vertical dashed lines — Brand 2 launch dates.



Note. Bars — actual monthly values. Dashed line — OLS linear trend. Dotted red — Brand 2 launch date.

Figure 4.3. Brand 1 Advertising Spend and Margin Trends

Source: developed by the author.

For Germany, both trends grow steadily ($p < .001$) — no signs of saturation. For Poland, margin grows year-over-year (+14.8% and +11.4%), however slope = 0.648 < 1 indicates sub-proportional advertising returns. No market shows a classical saturation point where increasing advertising leads to margin decline.

Table 4.3a. Advertising Expenditure and Contribution Margin Trends — Brand 1

Metric	PL Brand 1 (ads)	PL Brand 1 (marg)	DE Brand 1 (ads)	DE Brand 1 (marg)	Interpretation
Trend slope (€/month)	-289	+270	+576	+1,045	DE: both trends growing; PL: margin grows despite declining advertising
R ²	0.134	0.048	0.869	0.588	DE: strong linear trend; PL: weak

p-value	.009	.127	<.001	<.001	DE: statistically significant; PL: margin trend not significant
YoY margin 2023→2024	—	+14.8%	—	+31.8%	Margin growth confirmed in both markets
YoY margin 2024→2025	—	+11.4%	—	-1.0%*	*DE almost flat, not a decline

Source: developed by the author.

In Germany, both trends are statistically significant: advertising expenses +€576/month ($R^2 = .869$, $p < .001$), margin +€1,045/month ($R^2 = .588$, $p < .001$) — a typical pattern of active scaling. In Poland, Brand 1 margin grew year-over-year: +14.8% (2023→2024) and +11.4% (2024→2025), despite the budget decline in 2022–2023 due to operational changes.

4.2.2 Mechanisms for Reaching New Audiences

The trend analysis showed that Brand 1 did not reach classical saturation in any market; however, signs of sub-proportional efficiency were identified for Poland. This raises a question: what explains the total margin growth under the multi-brand model, if it is not compensating for exhausted potential? The data point to two complementary mechanisms.

First — algorithmic audience segmentation. Google and Meta algorithms, when launching new campaigns at different times, naturally form distinct seed audiences. Audience overlap between brands is less than 6% in all markets (Table 4.6), confirming that factually different buyers are being reached.

Second — price-based segmentation. Brand 1 is positioned in the premium price segment with over 20% exclusive content. Brand 2 and Brand 3 offer lower prices for the base catalog. Buyers with different price sensitivity naturally gravitate toward different brands regardless of the algorithm.

The overlap data were collected through the company's proprietary server-side cookie matching system — each browser received a unique identifier upon the first visit to any company website. This methodology does not depend on browser cookie isolation limitations.

4.2.3 Regression Analysis (Phase 1, Additional Evidence)

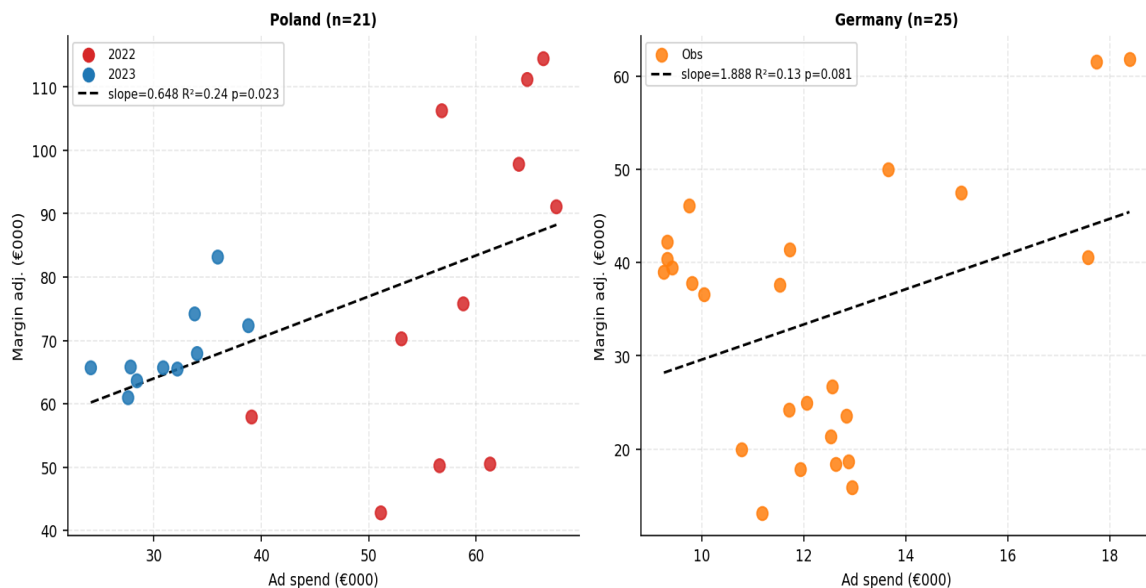
The following regression results are additional descriptive evidence, not the primary finding of RQ2.

Table 4.3b. Regression Analysis of Margin on Advertising (Phase 1)

Country	Specification	Equation / parameter	R ²	p-val.	Interpretation
Poland	Linear (n=21)	margin_adj = 0.242 + 0.648 × ads	0.242	.023	Significant; slope < 1 → sub-proportional
Poland	Log-log	β = 0.284	0.141	.094	β < 1, not significant
Poland	Quadratic	a ₂ = +11,049	0.369	—	a ₂ > 0: not confirmed
Poland	Spearman	ρ = 0.487	—	.025	Moderate positive correlation
Germany	Linear (n=25)	slope = 1.888	0.126	.082	Not significant
Germany	Log-log	β = 0.373	0.029	.416	β < 1, not significant
Czech R.	Linear (n=13)	slope = 3.106	0.765	<.001	Increasing marginal returns
Czech R.	Log-log	β = 2.556	0.882	<.001	β > 1 → increasing returns

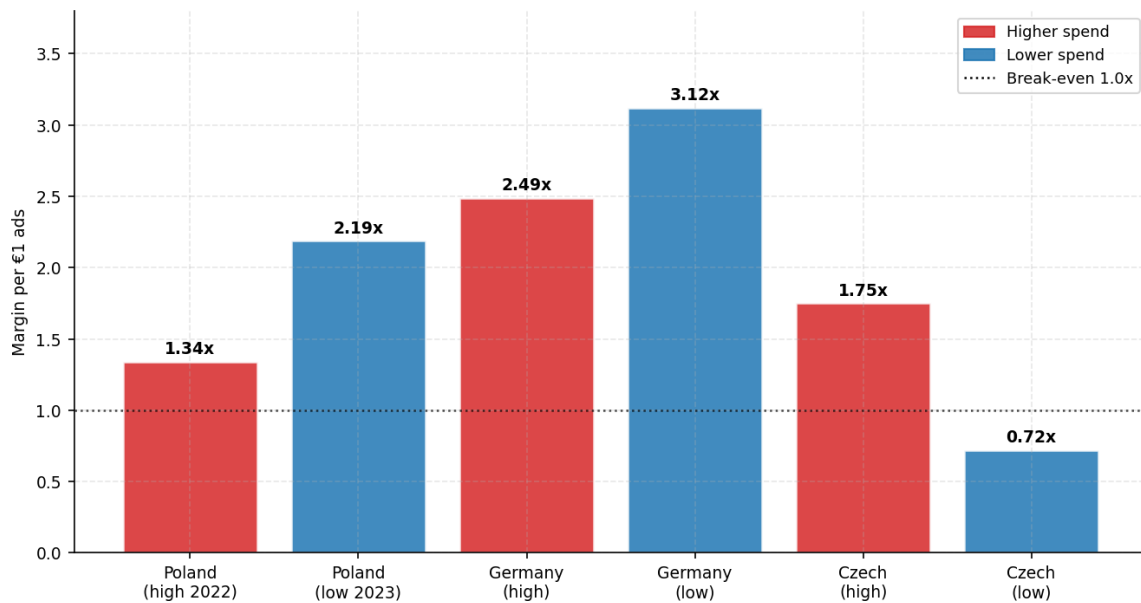
Source: developed by the author.

Figure 4.36. Advertising vs Margin (Phase 1)



Note. Scatter: advertising vs margin (Phase 1). Red — 2022, blue — 2023 (Poland). Dashed line — OLS regression.

Figure 4.3b. Advertising vs Margin (Phase 1)



Note. Margin/€ advertising by sub-period. Czech Republic shows increasing efficiency with larger budget — sign of an early-stage market.

Figure 4.4. Advertising Efficiency by Sub-Period

Source: developed by the author.

For Poland, the linear regression is significant ($p = .023$, slope = 0.648) and indicates sub-proportional returns: each additional €1 of advertising generates €0.65 in margin. The result must be interpreted cautiously: the budget decline in 2022–2023 coincided with the elimination of the call center and conversion funnel restructuring — the effects of advertising and operational changes cannot be separated. For Czech Republic, $\beta = 2.556$ ($p < .001$) — increasing marginal returns, consistent with an early-stage market. For Brand 3 in Poland, the 0.87x efficiency reflects the lower price per m²: lower margin per unit reaches the advertising break-even point more quickly. For Germany, no regression specification reached statistical significance (linear: $p = .082$; log-log: $p = .416$). The reason is the narrow budget range in Phase 1 (€9–18K/month) — insufficient variation for a reliable slope estimate. The direction of coefficients ($\beta = 0.373 < 1$) is consistent with sub-proportional returns but is not statistically confirmed.

4.3 Results for RQ3: Demand Cannibalization

4.3.1 Financial Analysis — Brand 2 Launch

Table 4.4 — before/after results for Brand 2 launch (windows: 10 months PL/CZ, 5 months DE).

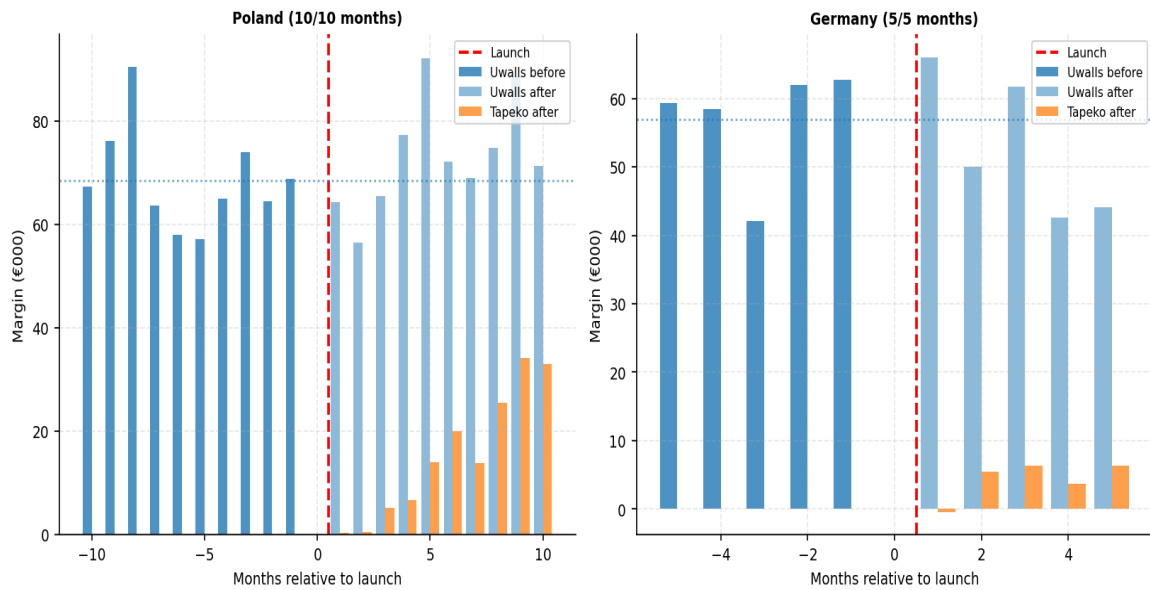
Table 4.4/ Brand 1 Metrics Before and After Brand 2 Launch

Metric	PL Before	PL After	DE Before	DE After	CZ Before	CZ After
Window (months)	10	10	5	5	9	9
Mean Brand 1 margin (€)	68,474	73,129	56,903	52,916	6,474	7,268
Mean Brand advertising (€)	131,388	31,379	16,483	20,912	3,770	1,654
Δ Brand 1 margin	—	+€4,655 (+6.8%)	—	-€3,987 (-7.0%)	—	+€794 (+12.3%)
Welch t-test p-value	—	.327	—	.529	—	.571
Mean Brand 2 margin (€)	—	15,304	—	4,262	—	1,677
Brand 2 margin/€ advertising	—	1.75x	—	1.04x	—	0.80x
Country margin increment	—	+€19,959/mo	—	+€275/mo	—	+€2,471/mo
Spearman ρ (Brand 2 ~ Brand 1)	—	+0.673 (p=.033)	—	-0.100 (p=.873)	—	-0.017 (p=.966)

Source: developed by the author.

The Welch t-test detects no significant changes in Brand 1 margin after Brand 2 launch in any market (all $p > .3$). In Poland, Brand 1 expenses remained unchanged (-€9/month), while the country margin grew by +€19,959/month — entirely attributable to Brand 2 (1.75x efficiency).

Figure 4.5 shows before/after results for Poland and Germany.



Note. Bars — contribution margin in thousands of EUR. Vertical line — Brand 2 launch month.

Figure 4.5. Brand 1 Margin Before and After Brand 2 Launch

Source: developed by the author.

4.3.2 Financial Analysis — Brand 3 Launch

Table 4.5 — before/after for Brand 3 launch (window 'before' = Phase 2, 'after' = Phase 3).

Table 4.5. Brand Metrics Before and After Brand 3 Launch

Metric	Poland	Germany	Czech Republic
Analysis window (months before/after)	10 / 19	5 / 20	9 / 13
Brand 1 margin before (€/month)	73,129	52,916	7,268
Brand 1 margin after (€/month)	79,398	59,285	6,950
Δ Brand 1 / p-value	+€6,270 / p=.249 □	+€6,369 / p=.324 □	-€318 / p=.733 □
Brand 2 margin before (€/month)	15,304	4,262	1,677
Brand 2 margin after (€/month)	17,214	9,127	2,829
Δ Brand 2 / p-value	+€1,910 / p=.664	+€4,865 / p=.016 □	+€1,152 / p=.013 □
Mean Brand 3 margin (€/month)	4,902	6,811	1,126
Brand 3 margin/€ advertising	0.87x □ □	1.05x	1.80x
Combined Δ (Ph2→Ph3)	+€13,081 (+14.8%)	+€18,045 (+31.6%)	+€1,960 (+21.9%)
t-test of combined margin	p=.146	p=.018 □	p=.081

Source: developed by the author.

Neither Brand 1 nor Brand 2 show a significant decline (Brand 1: all $p > .05$). Brand 2 significantly grew in Germany ($p = .016$) and Czech Republic ($p = .013$) — positive portfolio complementarity. Brand 3: 0.87x in Poland (lower price → lower margin per m² → faster advertising break-even); 1.05x and 1.80x in Germany and Czech Republic.

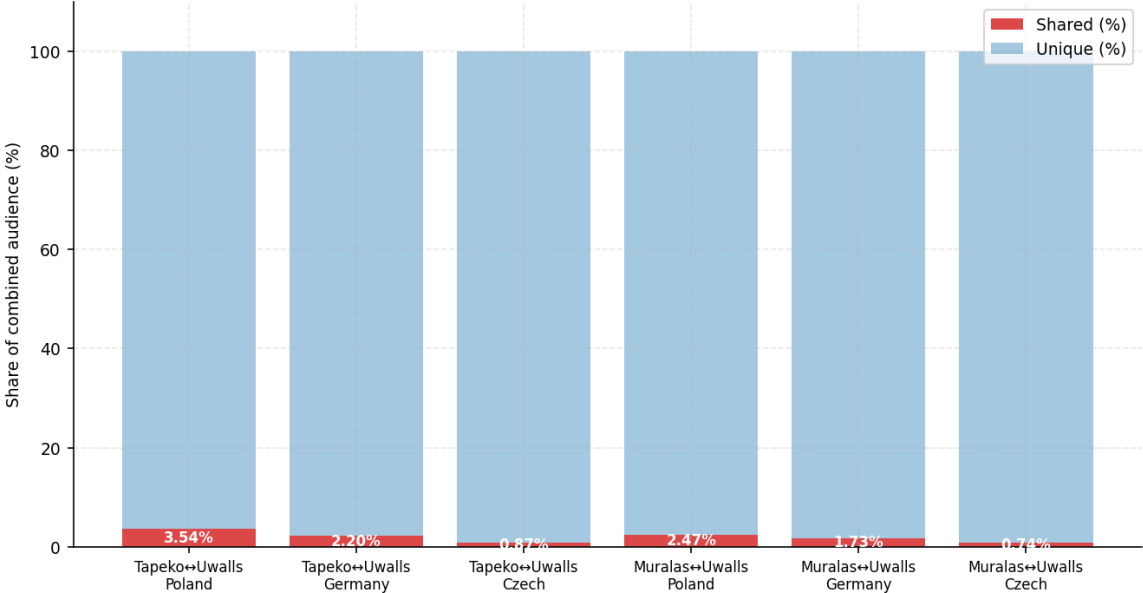
4.3.3 Audience Overlap Analysis

Table 4.6 and Figure 4.5 present audience overlap data between brands (server-side cookie matching).

Table 4.6. Audience Overlap Between Brands (Server-Side Cookie Matching)

Brand Pair	PL shared	PL overlap	DE shared	DE overlap	CZ shared	CZ overlap
Brand 2 ↔ Brand 1	13,272	3.54%	4,745	2.20%	719	0.87%
Brand 3 ↔ Brand 1	8,798	2.47%	3,416	1.73%	604	0.74%
Brand 3 ↔ Brand 2	7,167	5.23%	2,702	3.91%	255	3.56%

Source: developed by the author.



Note. Red segments — shared users (%). Blue — unique to each brand.

Figure 4.6. Audience Overlap (server-side cookie matching)

Source: developed by the author.

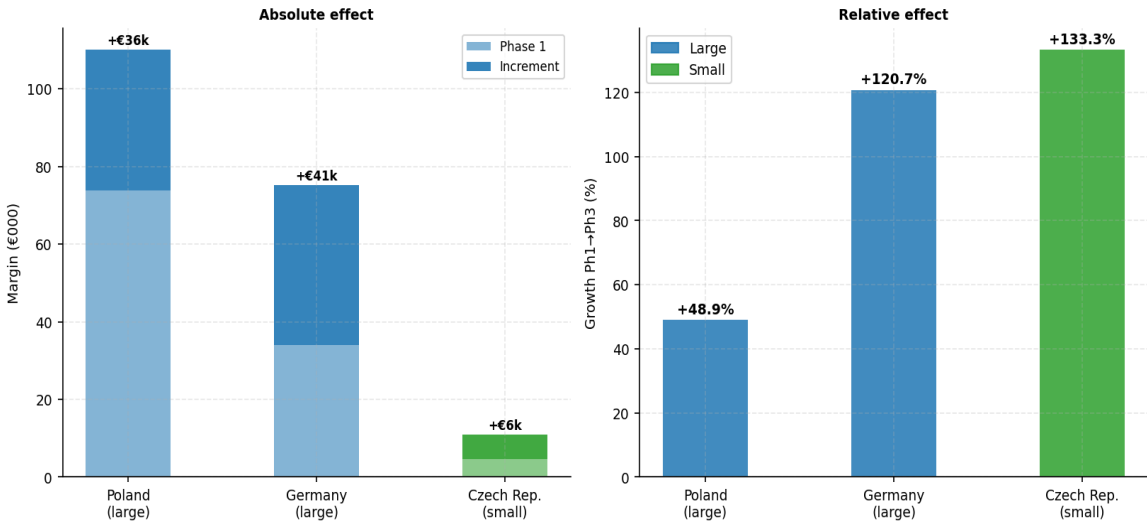
Overlap < 6% in all markets and brand pairs. Czech Republic — lowest (0.74–0.87%). 96.5% of the Brand 2 + Brand 1 Poland audience are unique users who visited only one site. Two mechanisms explain this: algorithmic segmentation (different launch timing → different seed audiences) and price-based segmentation (different price tiers → different buyers).

4.4 Results for RQ4: Market Size and Strategy Effectiveness

Table 4.7 and Figure 4.6 — cross-market comparison of large markets (PL, DE) and the small market (CZ).

Table 4.7. Cross-Market Comparison — RQ4

Metric	Large markets (PL + DE)	Small market (CZ)	Observation
Base margin Ph1 (mean/month)	€34,087 – €73,898	€4,675	Large markets 7–16× higher
Increment from 2nd brand	€14,534 – €23,091/mo	€4,269/mo	3–5× higher in absolute terms
Growth Ph1 → Ph3 (%)	+ 49% – +121%	+133%	Small market — larger relative effect
Significance Ph1 vs Ph3	p < .001 (both)	p < .001	Confirmed in all markets
Marginal returns (RQ2)	Sub-proportional Proportional	/Increasing (early stage)	Different maturity stage
Audience overlap	1.73% – 3.54%	0.74% – 0.87%	Lower in small market



Note. Left panel — absolute effect. Right panel — relative growth Ph1→Ph3.

Figure 4.7. Multi-Brand Strategy Effect by Market Size

Source: developed by the author.

Large markets generate a higher absolute increment (€14,534–€23,091/month vs €4,269/month in Czech Republic) due to a larger addressable audience pool. The small market shows a higher relative effect (+133% vs +49–121%) due to the low Phase 1 base. The effect is significant in all three markets ($p < .001$).

Important methodological caveat: three markets are insufficient for a formal statistical moderation test — RQ4 is a descriptive comparison, not a statistical test of a moderation hypothesis about market size effect. The Czech Republic counterfactual reveals an additional nuance: in Phase 2, the single-brand scenario would have been more profitable (–€1,150/month) due to Brand 1's increasing marginal returns (slope = 2.57) — indicating that the optimal timing for launching a second brand depends on the maturity stage of the existing brand in that specific market.

4.5 Chapter Summary

RQ1: Contribution margin grew in all three markets: +48.9% (PL), +120.7% (DE), +133.3% (CZ). Phase 1 vs Phase 3 — $p < .001$ in all countries. Counterfactual results are differentiated by market maturity stage. For Poland, the multi-brand model outperformed the single-brand scenario by +€8,861/month (slope = 0.648, $R^2 = 0.242$). For Czech Republic, the counterfactual shows the opposite: in Phase 2 the single-brand scenario would have been more profitable by €1,150/month due to Brand 1's increasing marginal returns in an early-stage market (slope = 2.570, $R^2 = 0.813$). However, the overall Phase 1→Phase 3 effect for Czech Republic remains the highest of all three markets (+133.3%, $p < .001$), confirming the long-term additive nature of the strategy. For Germany, no counterfactual was built due to the statistically insignificant Phase 1 regression ($p = .082$, $R^2 = 0.126$).

RQ2: Trend analysis shows that no market exhibits classical saturation (where increasing advertising leads to a margin decline). However, results are differentiated: for Poland, sub-proportional returns were identified (slope = 0.648 < 1) — budget increases are accompanied by disproportionately smaller margin growth, indicating proximity to the zone of declining efficiency; for Germany, both trends grow in parallel ($p < .001$) — no signs of saturation; for Czech Republic, increasing returns (slope = 2.57) confirm an early-stage market. Margin growth in the multi-brand model is explained by two mechanisms: algorithmic segmentation (different launch timing) and price-based segmentation (different positioning). H2 is confirmed via Poland's counterfactual (+€8,861/month).

RQ3: No significant changes in Brand 1 margin were found after any launch in any market (all $p > .05$). The largest absolute decline — Brand 1 in Germany after Brand 2 launch (−€3,987, −7.0%) — remained statistically insignificant ($p = .529$). Brand 2 significantly grew after Brand 3 launch in Germany ($p = .016$) and Czech Republic ($p = .013$) — indicating positive portfolio complementarity. Maximum overlap — 5.23% (Brand 3 ↔ Brand 2, Poland); for pairs involving Brand 1 — 3.54%. H1 (absence of cannibalization due to algorithmic and price-based segmentation) not rejected □.

RQ4: Large markets (Poland, Germany) generate a higher absolute increment (€14–23K/month vs €4K/month in Czech Republic) — due to a larger addressable audience pool allowing algorithmic segmentation to find more unique buyers. The small market shows a higher relative effect (+133% vs +49–121%) due to the low Phase 1 base. The effect is statistically significant in all three markets ($p < .001$). An important nuance for small markets: the Czech Republic counterfactual shows that in Phase 2 the single-brand scenario would have been more profitable due to Brand 1's increasing marginal returns — indicating that the optimal timing for launching a second brand depends on the maturity stage of the existing brand in that specific market.

Hypotheses: H1 (absence of cannibalization due to algorithmic and price-based segmentation) is not rejected — a necessary condition for confirming H2. H2 (additive contribution margin increment) is confirmed for Poland via counterfactual assessment (+€8,861/month) and for all three markets via between-phase comparison (Phase 1 vs Phase 3, $p < .001$ in all countries). An important nuance: for Czech Republic in Phase 2, the single-brand scenario would have been more profitable in the short term (−€1,150/month) — indicating that H2 fully materializes only when the existing brand has moved beyond the zone of increasing marginal returns. Both hypotheses together confirm that the multi-brand strategy is additive, not substitutive, in an algorithmic advertising auction.

CHAPTER 5

CONCLUSIONS

5.1 Answers to Research Questions

RQ1. Contribution margin grew in all three markets: Poland +48.9%, Germany +120.7%, Czech Republic +133.3% (Phase 1 vs Phase 3, $p < .001$). The counterfactual assessment for Poland shows that the multi-brand model outperformed the single-brand scenario by +€8,861/month (slope = 0.648). For Czech Republic in Phase 2, the single-brand scenario would have been more profitable by €1,150/month due to Brand 1's increasing marginal returns (slope = 2.57) — however, the overall Phase 1→3 effect remains the highest (+133.3%). For Germany, no counterfactual was built ($p = .082$, $R^2 = 0.126$).

RQ2. No market showed classical saturation. Results are differentiated by maturity stage: Poland (mature) — sub-proportional returns (slope = 0.648 < 1); Germany (developing) — parallel growth of advertising and margin ($p < .001$); Czech Republic (early) — increasing returns (slope = 2.57 > 1). Margin growth is explained by algorithmic and price-based segmentation. H2 is confirmed via Poland's counterfactual.

RQ3. Price cannibalization did not materialize in any market. Brand 1 margin changes after launches are statistically insignificant (all $p > .05$). Brand 2 significantly grew after Brand 3 launch in Germany ($p = .016$) and Czech Republic ($p = .013$) — positive portfolio complementarity. Maximum audience overlap — 5.23% (Brand 3 ↔ Brand 2, Poland); for pairs involving Brand 1 — 3.54%. H1 not rejected □.

RQ4. Large markets (Poland, Germany) generate a higher absolute increment (€14–23K/month vs €4K/month in Czech Republic) due to a larger addressable audience pool. The small market shows a higher relative effect (+133% vs +49–121%) due to the low Phase 1 base. The effect is statistically significant in all three markets ($p < .001$). An important nuance: in early-stage markets the single-brand scenario may be more profitable in the short term — indicating that the optimal timing for launching a second brand depends on the maturity stage of the existing brand.

Hypotheses. H1 not rejected — a necessary condition for H2. H2 confirmed for Poland (+€8,861/month) and for all markets (Phase 1 vs Phase 3, $p < .001$ in all countries). Both hypotheses together confirm the additive, not substitutive, nature of the multi-brand strategy.

5.2 Theoretical Implications

The results make several contributions to the theory of digital advertising markets.

First, the additive nature of the multi-brand strategy in the algorithmic auction is empirically confirmed, contrary to the expectations of cannibalization theories (Blake et al., 2015; Shriver & Bollinger, 2022).

Second, the mechanism of algorithmic audience segmentation as a factor preventing price cannibalization was proposed and tested. Overlap did not exceed 5.23% between any brand pair (3.54% for pairs with Brand 1) — an original contribution to understanding competition between co-owned brands.

Important limitation of the second contribution. *It should be acknowledged that while the study observes the outcome of absent cannibalization (low audience overlap), it cannot isolate the relative contribution of algorithmic segmentation versus price-based segmentation as the causal mechanism — both operate simultaneously and cannot be disentangled with the available data. The attribution of low overlap to algorithmic segmentation remains a theoretical interpretation, not a directly tested causal claim.*

Third, the concept of brand maturity stage was introduced as a moderator of multi-brand strategy effectiveness: Poland (sub-proportional), Germany (proportional), Czech Republic (increasing). This supplements brand portfolio theory (Yu, 2020) with a stage-based decision criterion.

Fourth, the current absence of cannibalization is not a permanent guarantee. Content differentiation between brands is a structural long-term protection — independent of algorithm evolution.

5.3 Practical Recommendations

1. Use brand maturity stage rather than waiting for saturation. Poland met the criteria: slope < 1, stabilizing YoY, mature funnel. Czech Republic did not (slope = 2.57). For new Company X markets where Brand 1 is still in the zone of increasing returns — prioritize the existing brand.

2. Maintain price differentiation between brands. Convergence of Brand 1 and Brand 2 price levels increases the risk of buyer price comparison and potential cannibalization.

3. Begin Brand 2 content differentiation preventively. The current protection — algorithmic segmentation — may weaken over time. A dedicated design team for Brand 2 is structural protection: unique content makes direct price comparison between brands impossible. Brand 3 — maintain as a budget brand without content investment.

4. Monitor overlap between brands monthly. Current maximum — 5.23% (Brand 3 ↔ Brand 2, Poland); for pairs with Brand 1 — 3.54%. Growth above 15% — a signal to review strategy. Use the existing cookie matching system with monthly aggregation.

5.4 Research Limitations

- Single company and niche segment. Data come from one company in one product category. External validity to other industries requires separate verification.
- Three markets. Insufficient for formal conclusions about the moderating effect of market size.
- Confounders in Poland. Funnel restructuring in 2022–2023 precludes clean advertising attribution for RQ2.
- Retrospective design. Natural quasi-experiment does not exclude external confounders. Results are associative rather than strictly causal.
- Short Phase 2 in Germany. 5 months limits statistical power of the before/after analysis.
- Limited overlap horizon. Server-side cookie matching data are available only for the last 6 months of the study horizon. The dynamics of overlap over time — in particular whether it grows after each launch — remain unknown. Cannibalization may be delayed: algorithms gradually expand audience pools and overlap may grow 12–18 months after launch. Current data do not capture this.
- Aggregated advertising data. No breakdown by Google/Meta platform.

5.5 Directions for Future Research

1. Brand maturity stage framework for new Company X markets. Slope, YoY dynamics and operational maturity as quantitative thresholds for the second brand launch decision — for the Baltic states, Romania, Slovakia.

2. Dynamic overlap tracking. At what overlap level does algorithmic segmentation cease to protect? Monthly monitoring across all Company X markets.

3. Impact of Brand 2 content differentiation on overlap with Brand 1. Test 12–18 months after launching a dedicated design team.

4. Conditions for launching a fourth brand. Will a fourth brand generate additional margin — or does cannibalization begin due to exhausted differentiation?

5. Analysis by advertising platform. Decomposition into Google Search, Shopping and Meta — where does natural audience separation between brands occur, and which platform contributes more to algorithmic segmentation.

5.6 General Conclusion

This study answers the question that lay behind Company X's decision: is the multi-brand strategy justified and does the risk of price cannibalization materialize between brands with different positioning but partially overlapping catalogs?

The answer is clear: the multi-brand strategy is additive, not substitutive. New brands increased total contribution margin on top of the growing Brand 1. Cannibalization did not materialize in any of the three markets — the maximum overlap between any brand pair did not exceed 5.23%, and for pairs with Brand 1 — 3.54%. Algorithmic and price-based segmentation together explain this result, though their relative contributions cannot be disentangled with the available data.

At the same time, the study reveals an important nuance: the effectiveness of the strategy depends on the maturity stage of the incumbent brand. In early-stage markets, launching a second brand may be premature in the short term. The launch decision should be based on a proactive assessment of brand maturity — not on waiting for saturation. The current absence of cannibalization is not a permanent guarantee: content differentiation between brands is strategic protection for the future.

REFERENCES

- Aggarwal, G., Badanidiyuru, A., Balseiro, S. R., Bhawalkar, K., Deng, Y., Feng, Z., Goel, G., Liaw, C., Lu, H., Mahdian, M., Mao, J., Mehta, A., Mirrokni, V. S., Paes Leme, R., Perloth, A., Piliouras, G., Schneider, J., Schwartzman, A., Sivan, B., Spendlove, K., ... & Zuo, S. (2024). Auto-bidding and auctions in online advertising: A survey. *ACM SIGecom Exchanges*, 22(1), 159-183. <https://doi.org/10.1145/3699824.3699838>
- Almestarihi, R., Ahmad, A. Y. A. B., Frangieh, R., Abu-AlSondos, I., Nser, K., & Ziani, A. (2024). Measuring the ROI of paid advertising campaigns in digital marketing and its effect on business profitability. *Uncertain Supply Chain Management*, 12(2), 1275-1284. <https://doi.org/10.5267/j.uscm.2023.11.009>
- Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica*, 83(1), 155-174. <https://doi.org/10.3982/ECTA12423>
- Chen, H., Chen, Y. J., Li, Y., Zhang, X., & Zhou, S. X. (2025). Digital goods reselling: Implications on cannibalization and price discrimination. *Production and Operations Management*, 34(7), 1725-1742. <https://doi.org/10.1177/10591478241305333>
- Chen, Y. (2023). Coordinated dynamic bidding in repeated second-price auctions in online ad markets. *Proceedings of Machine Learning Research*, 202. <https://proceedings.mlr.press/v202/chen23ac/chen23ac.pdf>
- Deng, Y., Mahdian, M., Mao, J., Mirrokni, V., Zhang, H., & Zuo, S. (2024). Efficiency of the generalized second-price auction for value maximizers. *ACM Transactions on Economics and Computation*. <https://doi.org/10.1145/3589334.3645360>
- Edelman, B., Ostrovsky, M., & Schwarz, M. (2007). Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords. *American Economic Review*, 97(1), 242-259. <https://doi.org/10.1257/aer.97.1.242>
- Guenther, P., Guenther, M., Rahman, M., Koval, M., & Iurkov, V. (2025). Advertising in business markets: The obscured bottom-line effect and need for appropriate analytics. *Industrial Marketing Management*, 126, 185-196. <https://doi.org/10.1016/j.indmarman.2025.02.003>
- Jeziorski, P., & Segal, I. (2015). What makes them click: Empirical analysis of consumer demand for search advertising. *American Economic Journal: Microeconomics*, 7(3), 24-53. <https://doi.org/10.1257/mic.20100119>
- Kim, D., & Pal, P. (2023). Nonparametric estimation of sponsored search auctions and impacts of ad quality on search revenue (CESifo Working Paper No. 10312). CESifo. https://www.ifo.de/DocDL/cesifo1_wp10312.pdf

- Kumar, V., Kotler, P., & Rajan, B. (2026). Whether, when and how to brand: A framework for strategic branding decisions for new-age technologies. *European Journal of Marketing*, 60(2), 337-368. <https://doi.org/10.1108/EJM-04-2025-0299>
- Lewis, R. A., & Rao, J. M. (2015). The unfavorable economics of measuring the returns to advertising. *The Quarterly Journal of Economics*, 130(4), 1941-1973. <https://doi.org/10.1093/qje/qjv023>
- Meyer, T., Kerkhof, A., Cennamo, C., & Kretschmer, T. (2024). Competing for attention on digital platforms: The case of news outlets. *Strategic Management Journal*, 45(9), 1731-1790. <https://doi.org/10.1002/smj.3600>
- Mueller, M., & Swoboda, B. (2025). Effects of international e-commerce firms' depth versus breadth of control on foreign sales performance and the role of market size and growth as context factors. *Management International Review*, 65, 275-304. <https://doi.org/10.1007/s11575-025-00570-y>
- Organisation for Economic Co-operation and Development. (2021). Competition in digital advertising markets. OECD Publishing. <https://doi.org/10.1787/f2209674-en>
- Platzek, F., Schmitz, A. K., Fassnacht, M., et al. (2025). The Yin and Yang of brand portfolio transformations: How conscientious lighthouse brands drive sustainability in organisations. *Journal of Brand Management*, 32, 400-417. <https://doi.org/10.1057/s41262-025-00393-0>
- Rashid, A., Spry, L., & Pich, C. (2024). A proposed brand architecture model for UK fashion brands. *Journal of Brand Management*, 31, 516-528. <https://doi.org/10.1057/s41262-024-00358-9>
- Sharabati, A. A. A., Ali, A. A. A., Allahham, M. I., Hussein, A. A., Alheet, A. F., & Mohammad, A. S. (2024). The impact of digital marketing on the performance of SMEs: An analytical study in light of modern digital transformations. *Sustainability*, 16(19), 8667. <https://doi.org/10.3390/su16198667>
- Shriver, S. K., & Bollinger, B. (2022). Demand expansion and cannibalization effects from retail store entry: A structural analysis of multichannel demand. *Management Science*. Advance online publication. <https://doi.org/10.1287/mnsc.2022.4308>
- Teng, L., Xie, C., Huang, X., & Ma, J. (2025). The effects of dual-oriented branding strategies on brand equity through innovation investment. *Journal of Business Research*, 190, 115235. <https://doi.org/10.1016/j.jbusres.2025.115235>
- Xu, L. (2025). A clustering method for product cannibalization detection using price effect. *Electronics*, 14(15), 3120. <https://doi.org/10.3390/electronics14153120>

- Yan, J., & Yuan, P. (2025). Corporate marketing intensity, market competition, and strategic aggressiveness. *Finance Research Letters*, 108226. <https://www.sciencedirect.com/science/article/abs/pii/S1544612325014813>
- Yilmazel, S. E., & Ozer, L. (2022). Brand portfolio strategies effects on consumers' attitude. *Marketing Intelligence & Planning*, 40(1), 138-152. <https://doi.org/10.1108/MIP-06-2021-0204>
- Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.
- Yu, J. (2020). A model of brand architecture choice: A house of brands vs. a branded house. *Marketing Science*, 40(1), 147-167. <https://doi.org/10.1287/mksc.2020.1245>
- Zhu, X., Chen, Y., Ren, M., & Chu, W. (2025). Is blockchain really good for e-platform? A double-edged sword from consumer trust and channel cannibalization. *Managerial and Decision Economics*, 46(4), 2562-2582. <https://doi.org/10.1002/mde.4482>