Modeling Retail Performance Through Consumer Behavior: Evidence from Multiformat, Multichannel, and Platform Settings

Thesis

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1 Prologue

Even if you are reading this, chances are you might not dig through every page of this thesis, and that's perfectly fine. We are all busy, right? Academics are busy working on papers (publish or perish!), and folks in industry are swamped with back-to-back meeting and projects (because bills do not pay themselves). But stick with me for just this short prologue.

Over the past five years, I have been deeply involved in retail analytics through my PhD. The questions I ask might sound familiar: Why do discounts work better in some stores than others? How does launching an online channel shift customer behavior? What happens to engagement on digital platforms during a crisis like COVID-19? These are questions that retailers and us (as consumers) ask all the time. What sets this work apart is my ability (and privilege) to spend half a decade exploring these questions with solid data, structured models, and consumer behavior theory to help connect the dots between observed patterns and strategic outcomes.

In this thesis, I look at how retailers adapt their pricing, channel, and platform strategies, together with, how customers respond in ways that impact sales, profits, and engagement. With the help of data and theory, I try to figure out what works, where, and why.

Here's what you'll discover.

1. **Multiformat: Pricing Strategy and Store Contexts**

   It's not just about choosing a price, it is about knowing how different customers respond to that price depending on where they shop. In two studies, I examine how pricing affects consumer behavior across different physical store formats including hypermarket, supermarket and convenience store. The first study looks at private label tiers, basic, standard, premium, and finds that their sales and profit elasticity vary significantly depending on the store format. The second study compares regular price reductions with promotional price discount, showing that the same price cut can produce very different effects depending on the context.
2. **Multichannel: The Long-Term Impact of Going Online**

   The digitalization become an inevitably strategy for retailer. But what actually happens when a traditional grocery retailer adds an online channel? In the third study, I investigate how online channel adoption changes customer behavior over the long run. The study finds that online adoption leads to long-term changes: larger basket sizes, increased spending in bulky or heavy categories like pet food and bottled water, and reduced purchases in impulse-driven or perishable items like snacks and fresh vegetables. These shifts reflect stable changes in how customers allocate effort and convenience across channels. Rather than cannibalizing in-store sales, online channels can enhance overall customer value

3. **Platform: Engagement, Visibility, and External Shocks**
   On digital platforms, success is not just about having a great product. It is about being seen. Visibility depends on curation systems: algorithms, recommendations, and editorial decisions that determine what content or products get seen (and consumed). In the final study, I examine how these dynamics shifted during the COVID-19 pandemic using follower growth on Spotify playlists as a case in point. The results show that playlists curated by the platform remained resilient, while those associated with major labels or superstar artists lost momentum. The takeaway is broader than music. In algorithmic environments where attention is scarce, resilience comes from diversified offerings, mid-tail strategies, and institutional curation, not just a sole product power or influence. For retailers operating on digital platforms, this highlights the importance of visibility management and content strategy, especially during periods of uncertainty.

As you flip through the pages of this thesis, you will come across some mathematical notations, statistical models, and theoretical discussions. It might not be everyone's cup of tea, but that is what academics thrive on; building on past research, applying theories to explain real-world phenomena, and using mathematical formula as a precision tool to quantify observations and draw conclusions. Don't worry, these theoretical discussions and equations are here to help us figure out how pricing, platforms, and behavior all fit together. It is more like assembling a building where theory is the blueprint, data are the raw materials, and models are the tools used to put it all together into something useful, long-lasting and structurally sound.

Final Thought: This thesis is not a definitive guide to retail strategy. What I have offered here is a series of observations, tests, and tentative conclusions drawn from data. The value is not just in the answers, but in the act of asking: looking closely, questioning assumptions, explaining patterns. I hope to show that doing research is less about undeniable truths and more about honest attempts. Attempts to understand, to explain, to make sense of a world that is constantly shifting, sometimes so dramatically that it breaks whatever model that was in development. And in the end, maybe that's the real strategy: stay curious, stay skeptical, and never trust a finding that required three robustness checks and a prayer.

2 Introduction

2.1 Background

Growing multichannel and digital offerings and increased data availability are major developments that have characterized the retail sector in the past decades (Bradlow et al., 2017; T. H. Cui et al., 2021; Dekimpe, 2020; van Heerde & Dekimpe, 2024; Verhoef et al., 2010). These advancements have allowed consumers to have more access to various stores' formats. These formats include traditional physical stores (brick-and-mortar), online-only retailers (click-only , and multichannel retailing[1], where retailers offer their goods and services both in physical stores and online (brick-and-click). For example, a brick-and-mortar format may include a grocery store where customers shop in person using carts in physical aisles. A click-only format may resemble Amazon's early model, when it exclusively sold books online. A brick-and-click retailer could be a fashion brand where customers browse or buy items either through a website or in a physical store. As consumers increasingly use multiple formats, retailers gain more data to better understand customer decisions and improve performance evaluation across channels.

With alternative store format(s) and/or channel(s), retailers can offer various access for and communicate to broader customers and enhance their shopping experience (Verhoef et al., 2015). Particularly, different retail formats and channels can facilitate different shopping goals within the same customers or customers with different characteristics and/or shopping behaviors. Thus, it is beneficial for retailers to understand how customers behave differently across formats/channels and how these customers are different in terms of their demographic factors and/or purchasing behaviors (Verhoef et al., 2010). These understandings lead to important implications for retailers to effectively design and customize their marketing mix with respect to their customers' needs (Breugelmans, Altenburg, et al., 2023)

Retailing settings are abundant with data. They have both macro-level data (e.g., total grocery purchases from particular demographic groups, total number of global users in the platforms) and micro-level data (e.g., an individual or household purchase of certain categories, a consumption history of a user). Multichannel retailers generally have comprehensive information regarding products (what was bought), customers (who bought), channels (how it was bought), time (when it was bought) and locations (where it was bought from or delivered to) to

[1] Throughout this thesis, I refer to such settings as multichannel retailing where physical and digital channels operate in parallel but are not necessarily integrated into a seamless customer shopping experience, as in omnichannel retailing (Verhoef et al., 2015).

understand their customer thoroughly and efficiently optimize their operations (Bradlow et al., 2017; van Heerde & Dekimpe, 2024). Digital platforms, such as Spotify (streaming service) or eBay (online marketplace), also operate as retailers by offering products or services directly to consumers, often without physical constraints. They can leverage detailed customers data that allow them to produce better products (e.g. media contents) and enhance customers' loyalty respectively (Smith & Telang, 2016). In addition to data directly collected by retailers, publicly available information from the internet (i.e., web data) can be extracted via web scraping or application programming interfaces (APIs) to generate further insights. These web-based data sources offer valuable context for understanding the market, customer behavior, and competitive positioning across retailers (Boegershausen et al., 2022; Guyt et al., 2024).

These developments offer both opportunities and challenges for retailers and researchers. On one hand, the diversity of retail formats allows businesses to tailor offerings to different consumer segments and shopping contexts. For example, as Forbes (2024) highlights, leading retailers are shifting from a one-size-fits-all model to becoming "support partners" for different shopper groups by customizing store formats, product assortments, and services to meet the specific needs of segments such as Gen Z, millennials, and diverse cultural communities. On the other hand, the volume and complexity of available data demand a more structured, theory-driven approach to uncover meaningful insights. For example, KPMG (2025) notes that leading retailers move beyond ad-hoc or intuition-based decisions by developing data strategies built on formal, best-practice frameworks. This structured approach ensures that data interpretation consistently aligns with clear business objectives and minimizes individual bias.

Understanding consumer behavior, designing effective pricing strategies, and evaluating performance across channels now require a deeper integration of insights from consumer behavior research, empirical methods, and analytics. In this context, these insights act as a lens to interpret the observed patterns revealed by data, while data sharpens that lens by validating assumptions and uncovering causal relationships. Data thus becomes not just a tool for operational improvement, but a means to systematically quantify how consumers respond to strategic decisions and how those responses translate into retail performance.

2.2 Problem Formulation

Despite major advancements in data collection and retail infrastructure, translating these capabilities into actionable insights about performance remains far from straightforward. Retailers and platforms still face several challenges in evaluating the outcomes of their strategic decisions, especially when trying to do so through the lens of consumer behavior, which often involves complex, context-specific responses that are difficult to isolate and interpret. As consumer responses can vary widely across retail environments, retailers must go beyond tracking what happened to understand why it happened, and eventually how it matters for future decisions. Doing so requires an approach that integrates empirical analysis with established insights from consumer behavior literature to uncover patterns that are both theoretically sound and practically relevant.

First, the growing reliance on data-driven approaches has not always been matched by the integration of theory. Retailers and researchers have access to vast volumes of behavioral data, from individual shopping trips in physical stores to digital engagement metrics on online platforms. However, more data does not inherently mean more insight generated. Without clear theoretical grounding, analysis can become reactive or descriptive at best. In other word, the analysis focuses on what happened, but not why. For example, a spike in sales following a price change might be observed, but without an understanding of reference price effects or shopper context, the implications for future pricing strategy remain unclear. As emphasized by Bradlow et al. (2017) and Dekimpe (2020), the challenge lies in combining empirical evidence with underlying mechanisms that explain *why* certain patterns emerge, *when* they matter, and *how* they generalize across contexts. In the absence of such integration, managerial decisions risk being guided by surface-level correlations rather than actionable guidance grounded in causal understanding and applicable across strategic settings.

Second, differences across store formats introduce challenges for both analysis and strategic execution. Even within the same retail chain, hypermarkets, supermarkets, and convenience stores cater to distinct shopping missions and customer expectations.. For example, a consumer may visit a hypermarket for planned, bulk shopping and a convenience store for quick, habitual purchases. Despite these differences, retailers often apply uniform standardized pricing and promotions across formats, without fully accounting for how the same customer may respond differently depending on the setting. This creates uncertainty about the effectiveness of pricing strategies and raises a broader challenge: how should retailers design and evaluate pricing decisions when consumer responses vary by format?

Third, when physical retailers introduce an online channel, it creates strategic uncertainty about long-term customer behavior and business outcomes. While digital channels often increase convenience and expand access, they also influence how consumers interact with the retailer over time. Some customers may shift their purchase volume online, while others may change product mix, basket size, or engagement frequency. These behavioral shifts make it difficult to assess whether online channel initiatives effectively enhance long-term customer value or overall performance. The broader challenge is to isolate and quantify how such adoption changes purchasing behavior over time, such as visit frequency, basket size, or category choices, in ways that impact retailer revenue and profitability.

Fourth, consumer engagement on digital platforms is increasingly influenced by curation systems that determine which products, assortments, or content receive exposure. In click-only environments like music streaming platforms, algorithmic and editorial curation shapes what users see and interact with. These systems can either amplify already-popular items or give visibility to emerging or independent content providers. Similar mechanisms exist in digital retail. For example, search results on e-commerce sites are ranked by relevance and popularity, recommendation engines suggest products based on browsing or purchase history, and curated landing pages, like "Top Deals" or "Editor's Picks" highlighting selected items. These tools collectively shape which products are noticed and ultimately purchased. This creates practical challenges for brands, sellers, or creators who compete for limited consumer attention, and makes it harder for platforms and their participants to anticipate which items will succeed. External shocks, such as the COVID-19 pandemic, can shift user behavior and content consumption patterns, indirectly affecting who gains or loses (more or less) visibility. The broader challenge is to understand how platform design and curator roles influence performance outcomes, particularly in contexts where attention is scarce and competition is high.

Together, these challenges point to a broader need to understand how strategic retail decisions affect business performance by accounting for how consumers perceive, interpret, and respond to those decisions. This thesis responds to that need by examining how pricing strategies, channel additions, and digital exposure influence sales, profitability, and engagement, drawing on established consumer behavior literature and applying empirical models to large-scale data.

2.3 Research Purpose and Questions

The purpose of this thesis is to examine how strategic retail decisions including pricing, channel introduction, and platform-based engagement, affect performance outcomes through their influence on consumer behavior. By empirically modeling consumer responses across multiformat retailing, multichannel retailing, and digital platforms, the thesis demonstrates how data-driven approaches informed by consumer behavior research can generate actionable insights into sales, profitability, customer value, and engagement.

This leads to the overarching research question:

How do strategic retail decisions, particularly in pricing, channel introduction, and digital engagement, affect consumer behavior, retailer performance, and stakeholder outcomes across different retail settings?

The thesis addresses this question through four empirical studies, each aligned with a specific sub-question:

1. How do pricing strategies among multitier private labels tiers affect sales and profitability across different store formats within the same retail chain?
2. How do regular price reductions and promotional discounts differentially affect sales outcomes across store formats?
3. What are the long-term effects of online channel adoption on customer behavior and retailer revenue?
4. How did the COVID-19 pandemic influence playlist follower growth on Spotify, and how did this vary across curators, content types, and popularity levels?

These studies address the challenges outlined in Section 2.2 by linking strategic decisions to consumer responses and performance outcomes across different retail environments. Studies 1 and 2 examine pricing effectiveness across store. Study 3 responds to the uncertainty surrounding online channel introduction by quantifying long-term changes in customer behavior and revenue. Study 4 disentangles the dynamics of digital platform engagement by analyzing how external disruptions, such as the pandemic, affect exposure and visibility for different stakeholders.

2.4 Outline of the Thesis

The remainder of this thesis is organized as follows. Chapter 3 introduces the theoretical framework, drawing on key concepts from consumer behavior research to guide the empirical investigations. Chapter 4 outlines the data sources and empirical methods used across the four studies, highlighting how different modeling approaches are applied in multiformat, multichannel, and digital platform contexts. Chapter 5 presents the four empirical studies, each corresponding to one of the research sub-questions, and discusses their individual contributions. Chapter 6 discusses the theoretical contributions, managerial implications, methodological considerations of this study as well as its limitations and suggestions for future research. Finally, the Epilogue presents a personal reflection on the research process including what was learned, what was messy, and what might still be worth questioning. For a high-level overview. Table 1 summarizes the four empirical studies with respect to their strategic focus, theoretical grounding, data, analytical level, and key performance outcomes. This provides a holistic outline for the theoretical and empirical content presented in Chapters 3 to 5.

Table 1 Overview of Empirical Studies by Strategic Decision, Theoretical Lens, Context and Performance Outcomes

Study	Strategic Decision	Key Research Focus	Theoretical Lens	Dataset & Coverage	Level of Analysis	Performance Outcome
1	Price Strategy Across Formats	How do pricing strategies among multitier private labels tiers affect sales and profitability across different store formats within the same retail chain?	Pricing theory, multiformat retailing, private label strategy	Retailer scanner data from 2014 - 2016	Weekly brand sales	Sales, profits
2	Price Strategy Across Formats	How do regular price reductions and promotional discounts differentially affect sales outcomes across store formats?	Reference price effects, price framing, consumer response	Retailer scanner data from 2014 - 2016	Weekly brand sales	Sales
3	Channel Introdution	What are the long-term effects of online channel adoption on customer behavior and retailer revenue?	Multichannel retailing, digital complementarity	Retailer scanner data from 2014 - 2019	Weekly customer purchases	Category purchases, revenues
4	Platform Engagement	How did the COVID-19 pandemic influence playlist follower growth on Spotify, and how did this vary across curators, content types, and popularity levels?	Platform economics	Web-scraped music streaming platform panel data from 2019 - 2020	Weekly playlist followers	Engagement (i.e., playlist followers)

3 Theoretical Background and Framework

Strategic retail decisions, such as pricing, channel design, or platform engagement, are no longer isolated or operational. They are deeply shaped by the retail context, consumer expectations, and digital systems that influence customer behavior. The challenge is not the lack of data, but the difficulty of interpreting consumer responses in a way that is both theoretically grounded and practically relevant. While retailers now have access to granular data, the meaning of those behaviors depends on the retail format and the way consumers process information. A promotion that works in one store format may fail in another. An online channel may increase convenience but alter long-term purchasing behavior unexpectedly. The same challenge applies to digital platforms, which increasingly serve as retail-like environments. Visibility and engagement are shaped not only by consumer choices but also by algorithmic and editorial curation, often amplifying some content while leaving the broader effects on behavior and stakeholder outcomes unclear. Across these domains, the key concern is the same: how consumers interpret and respond to strategic actions, and how those responses shape performance.

This chapter provides the theoretical background for understanding how strategic retail decisions translate into performance outcomes through consumer behavior. It draws on three core areas of marketing literature: 1) consumer response to pricing strategy across formats, 2) consumer decision-making and channel adoption in multichannel settings, and 3) consumer engagement and stakeholder influence on digital platforms. Rather than treating consumer behavior as a black box, this chapter frames it as the interpretive lens through which retailers' actions are understood and acted upon. While academic research often seeks to explain why consumers respond in certain ways, practical applications and some empirical work still focus primarily on measurable outcomes, what happened, rather than mechanisms that drive them. This thesis emphasizes the importance of reconnecting outcomes with the underlying mechanisms, recognizing that performance depends not only on what retailers do, but also on how consumers perceive and respond to those actions.

The remainder of the chapter is structured as follows. Sections 3.1 to 3.3 review theoretical insights across the three domains. Section 3.4 then synthesizes these perspectives into a consolidated table, highlighting conceptual tensions, literature gaps, and the contributions made by each empirical study in this thesis.

3.1 Consumer Response to Pricing Across Store Formats

Retailers operating across multiple store formats face a challenge: how to set and manage prices in a way that aligns with consumer expectations, drives sales, and preserves profitability, especially when shoppers may expect consistent pricing across locations operated by the same retailer. Store formats like hypermarkets, supermarkets, and convenience stores serve distinct shopping missions, which shape how consumers interpret and respond to pricing decisions. While retailers often differentiate prices according to format to reflect these shopping missions, consumer perceptions may not always align with these strategic distinctions, particularly when stores are located in close proximity or share branding

Traditionally, physical retail formats have been defined by differences in size, assortment depth, price levels, location, and convenience. Hypermarkets, for instance, tend to attract bulk shoppers and value seekers, while convenience stores appeal to quick trips and impulse needs. These format-driven missions affect how consumers interpret prices and respond to promotions. Haans and Gijsbrechts (2011) find that the same promotion can have different effects depending on the format, even within a single retailer. This variation is linked not only to differences in store missions but also to how consumers form and apply reference prices—internal benchmarks drawn from memory or expectations that influence how attractive a given price appears (Mazumdar et al., 2005; van Oest, 2013).

In the context of multiformat retailing, pricing decisions involve trade-offs between setting regular price levels and offering temporary promotional discounts (i.e., reduction in price). These two pricing mechanisms influence consumer behavior in different ways. Regular price cuts may reinforce value perceptions over time but erode margins if not carefully planned. Promotions, on the other hand, can stimulate short-term demand but may train consumers to delay purchases or expect deals. The strategic balance between these tools depends on the store format and customer base. For instance, consumers in hypermarkets may be more deal-driven and responsive to deep discounts, whereas those in convenience stores might be more time-sensitive and less price elastic (Weathers et al., 2015; Ailawadi et al., 2006).

From a retailer's perspective, the effectiveness of pricing strategies also varies across categories and brands. Some product categories (e.g., staples or frequently purchased items) may benefit more from everyday low pricing, while others (e.g., discretionary or seasonal items) respond better to promotions. As a result, retailers must tailor their overall pricing approach to reflect both format-specific consumer behavior and product-level characteristics that shape how price changes affect sales and profitability.

These prior studies inform and motivate the first two empirical papers in this thesis. While the literature has established that pricing outcomes vary across store formats, less is known about how multi-tier private label overall perform in different retail environments under the same retailer or how pricing strategies, including reducing regular prices versus offering promotions, influence consumer behavior at the format level. The first study addresses this gap by examining the format-specific responsiveness and profitability of private label tiers. The second investigates how the effectiveness of regular price changes and temporary promotions varies across categories, brand types, and store formats.

3.2 Consumer Decision-Making and Channel Adoption

The rise of online shopping has reshaped the retail landscape, giving rise to hybrid models where physical and digital channels coexist, commonly referred to as multichannel retailing. Unlike exclusively digital or physical formats, this multichannel structure introduces new complexities for retailers. For example, the same customer may shop in-store for certain needs, order online for others, and expect a consistent experience across both (e.g., Wang et al., 2015; Li et al., 2015). This creates challenges in managing customer relationships, aligning inventory and fulfillment across formats, and measuring performance over time. Retailers must integrate transaction records, browsing histories, and fulfillment data across channels to form a coherent picture of consumer behavior, and assess whether online adoption leads to sustained value creation or merely shifts spending to a costlier channel (Verhoef et al., 2015).

From a consumer perspective, channel choice is often modeled as a utility-maximizing decision (Ansari et al., 2008), where customers weigh trade-offs between convenience, assortment, price transparency, and immediacy. The same customer may pursue different shopping goals across channels, using online platforms for stock-up trips or product research while relying on physical stores for immediacy or tactile evaluation. These channel preferences are further shaped by situational factors such as trip purpose, time constraints, or promotional activity (Van Nierop et al., 2011; Neslin et al., 2006).

More specifically, the theory of shopping utility maximization (Campo et al., 2020) distinguishes between acquisition utility, which is benefits derived from the product itself, such as price or assortment, and transaction utility, which is benefits related to how easily and conveniently the product can be obtained. In grocery retail, where prices and assortments may remain similar across channels, the decision to purchase online or offline is often driven by perceived transaction utility. Online channels typically enhance convenience for certain categories (e.g., bulky or planned purchases) while reducing utility for others (e.g., products requiring tactile evaluation or freshness).

Thus, when retailers introduce an online channel, the performance implications are not always clear. On one hand, online access can enhance convenience, expand reach, and improve customer experience, potentially increasing retention or share of wallet (Verhoef et al., 2007). On the other hand, it can cannibalize in-store sales, especially when assortments and pricing are harmonized across channels (Avery et al., 2012; Gensler et al., 2007). While some shoppers expand their basket sizes or purchase new categories online, others show signs of reduced variety, lower engagement with impulse purchases, or even eventual disengagement, especially in low-involvement categories like groceries (Chintala et al., 2023).

While prior research has examined immediate changes in shopping behavior following online channel adoption, the long-term effects remain less understood. Most studies focus on focuses on short-term changes in activity (e.g., Wang et al., 2015; Campo et al., 2020), but fewer explore how behavior evolves over time, particularly among existing customers. A question for both retailers and scholars, therefore, is whether digital channel adoption generates incremental, sustainable customer value or merely shifts consumer spending toward an alternative channel, potentially reducing overall profitability. Although retailers may grapple with these questions in practice, empirical evidence on long-term effects remains scarce in the academic literature .

To address this gap, the third empirical study of this thesis examines how online channel adoption influences long-term purchasing behavior and retailer revenue generation within a local grocery context. Specifically, it investigates not only which customer segments adopt online channels and which product categories they shift toward but also whether these behavioral shifts persist over time, ultimately translating into sustainable value creation for retailers.

3.3 Consumer Engagement and Stakeholder Influence on Digital Platforms

As retail shifts into digital spaces, the mechanisms that govern consumer engagement increasingly diverge from traditional models. In brick-and-mortar environments, exposure is shaped by store environment such as shelf placement, store layout, and signage. On digital platforms, however, visibility is governed by algorithmic and editorial curation. Platforms such as Spotify, YouTube, Amazon, and eBay act not only as marketplaces but also as gatekeepers of influence, deciding which products, content, or sellers are surfaced. These systems structure what consumers see, click, and ultimately engage with, making exposure itself a central competitive resource (Goldfarb & Tucker, 2011; Chen et al., 2021).

In music streaming, for example, consumer attention is directed through curated playlists and recommendation algorithms that govern content discovery. Prior research has highlighted the dual role of platforms in both democratizing access and reinforcing popular products and contents: while theoretically capable of supporting long-tail diversity, algorithms tend to amplify popular content and reproduce visibility hierarchies (Anderson, 2006; Bar-Isaac et al., 2012; Aguiar & Waldfogel, 2021). Curators on platforms, whether platform-owned, label-affiliated, or independent, play a role that complements algorithmic systems by selectively organizing and promoting content. While algorithms primarily rely on user data and engagement patterns to shape visibility, curators introduce human judgment, editorial intent, and identity signaling into what users discover.

External shocks can affect these dynamics. The COVID-19 pandemic, for instance, shifted the consumption habits and changed the baseline for user engagement (e.g., Sim et al., 2022), yet it remains unclear how these shifts affected different stakeholders, particularly those involved in content curation. In the context of music streaming, playlist followers represent a key form of user engagement that can signal platform attention, imply consumption patterns, and shape revenue opportunities. However, follower growth is not evenly distributed across curator types. Platform-owned playlists often enjoy prominent placement and their own algorithmic support, while label-owned and independent curators face more variable exposure. These structural asymmetries can amplify existing inequalities, especially during the pandemic.

The fourth empirical study in this thesis addresses this ambiguity by analyzing follower dynamics across curator types on Spotify before and after the COVID-19 outbreak. In doing so, it contributes to a broader understanding of platform governance and stakeholder resilience, with implications for how influence is gained, maintained, or lost during periods of disruption. While this study focuses on music streaming, its findings extend to digital retail settings where the stakeholders (e.g., brands) are mediated by digital platform architecture and curation mechanisms. In both contexts, consumer engagement is affected by how products or content are visible. The stakeholders must compete within systems that combine algorithmic bias with editorial control. By analyzing how a large-scale disruption like the COVID-19 pandemic altered follower growth across curator types, the study contributes to a broader marketing literature concerned with how crises may impact attention allocation, competitive dynamics, and stakeholder outcomes on digital platforms.

3.4 An Integrated Framework Linking Theory and Empirical Studies

The three preceding sections reviewed distinct yet interconnected streams of consumer behavior in the marketing literature related consumers response to retailers' strategies. While each domain addresses different strategic decisions, they are unified by a shared emphasis on how consumers perceive, interpret, and respond to firm actions. These responses, whether in the form of purchase behavior, channel use, or platform engagement, eventually shape retail performance.

To make this logic explicit, the framework can be visualized as a simplified pathway:

Strategic Retail Decision -> Consumer Interpretation & Response -> Performance Outcome

This structure applies across all four studies in the thesis. Each study investigates how a particular strategic action alters the consumer decision-making context, and how that in turn affects key outcome variables such as sales, profitability, customer retention, or engagement. Table 2 summarizes the conceptual focus of each study.

Empirical Study	Strategic Retail Decision	Theoretical Framework	(Key) Consumer Mechanism	Performance Outcome
1	Setting price for multitier PLs across formats	Pricing theory, multiformat retailing, private label strategy	Customer relatively compared prices within multitier PLs and perceive differently	Sales, profits
2	Adjusting regular price or offering promotions across formats	Reference price effects, price framing, consumer response	Customer perceived changes in regular price and discounts differently.	Sales
3	Channel Introduction	Multichannel retailing, digital complementarity	Customers shift their behavior after adopting online channel and might not necessary retain this shift	Category purchases, revenues
4	Customer engagement on digital platforms	Platform economics	Customers have limited attention and needs to choose a certain contents to fit with the current situation.	Engagement (i.e., playlist followers)

This framework clarifies the thesis's central logic: strategic retail actions are subject to consumer interpretation, which in turn influences performance outcomes. Since these interpretations are context-dependent, empirical investigation is a key input to quantify and identify which extent the strategies succeed. Across the domains examined, the previous studies suggest that any shift in consumer perception such as price comparison, shopping utility, or content visibility, can have significant implications for retailer or stakeholder performance.

4 Methodology

This chapter outlines the empirical strategies used across the four studies in this thesis, each of which addresses a different aspect of strategic retail decision-making. Rather than introducing novel econometric methods, this chapter demonstrates how established quantitative techniques are implemented to three empirical contexts: multiformat retailing, multichannel retailing, and digital platforms. The chapter is organized into two main sections: the empirical data contexts and the modelling approaches. The overarching goal is to isolate how strategic retailer or platform decisions influence observable consumer responses and, in turn, performance outcomes.

The chapter is organized into two main sections. Section 4.1 describes the empirical data contexts, including data sources, sampling criteria, and key characteristics for our empirical studies. Section 4.2 outlines the modeling approaches, grouped by the level at which consumer behavior is aggregated and the type of performance outcome measured. Table provides a high-level summary of the four empirical studies, including context, data source, methodological approach, level of analysis, and performance outcomes.

Empirical Study	Context	Data Source	Method	Level of Analysis	Performance Outcome
1	Multiformat retailing	Retailer scanner data from loyalty program	Modelling retail performance using aggregate sales data	Weekly brand sales	Sales, profits
2	Multiformat retailing	Retailer scanner data from loyalty program	Modelling retail performance using aggregate sales data	Weekly brand sales	Sales
3	Multichannel retailing	Retailer scanner data from loyalty program	Modelling retail performance using individual purchase behavior	Weekly customer purchases	Category purchases, revenues
4	Digital platforms	Spotify playlist API and Web-scraped data	Modelling engagement outcomes on Digital Platforms	Weekly playlist followers	Engagement (i.e., playlist followers)

4.1 Empirical Contexts and Data Source

This thesis draws on three distinct empirical contexts to investigate how strategic retail decisions influence consumer responses and how consumer responses influence performance outcomes of the decisions respectively. The four empirical studies leverage rich and granular datasets from the domains of physical multiformat retailing, multichannel retailing, digital platforms. This section outlines the empirical setting and data characteristics for each context.

Multiformat Retailing (Studies 1 and 2)

The first two empirical studies are situated within the context of multiformat grocery retailing, examining how pricing strategies perform across different store formats from the same retailer, such as, hypermarkets, supermarkets, and convenience stores. Despite being the same retailer chain, these formats cater to distinct shopping missions and customer expectations, creating an appropriate context to explore consumer responses to pricing decisions across different physical stores.

The data come from the loyalty program of a major grocery retailer and include detailed transaction-level records for approximately 5,500 customers over 153 consecutive weeks (2014–2016), covering around 900,000 shopping trips. Each record contains product-level information, including brand, category, regular price, promotional discount, and quantity purchased. This level of granularity allows for detailed measurement of consumer behavior and pricing outcomes.

To ensure consistency and comparability, the analysis focuses on three store formats operated by the same retailer: hypermarkets (large-format stores catering to stock-up trips), supermarkets (medium-sized stores serving regular household needs), and convenience stores (small outlets focused on immediacy and proximity). While all formats belong to the same retail chain and share branding, they differ in several aspects such as store physical environment, assortment breadth, assortment depts, and price levels. These differences make them an appropriate context to examine how pricing strategies perform across formats.

The product sample was constructed to avoid biases introduced by assortment differences. Specifically, products were selected based on consistent availability across the entire observation period and across all three store formats, with an emphasis on frequently purchased brands. Only items with standardized package sizes were retained, for instance, converting soft drink volumes to a common unit (e.g., per 100ml), to ensure that any observed pricing effects were not confounded by size-based price differences. This approach mitigates the risk that format-based variation in sales is driven by differences in what is stocked, rather than how consumers respond to pricing.

This dataset enables the construction of comparable brand-level sales panels across formats. By observing which brands were purchased in each format, the two empirical studies can systematically investigate how sales and pricing effectiveness vary not just within a single format but across formats.

While the dataset focuses on loyalty card holders from a single retail chain, this consistent tracking allows for precise observation of behavioral shifts over time within a stable customer base. However, it does not capture purchases made at competing grocery retailers, which may limit broader generalizability. Still, this does not diminish the internal validity of the findings, as the aim is to understand format-specific consumer responses to pricing within a controlled multiformat setting. Potential confounds from unobserved external factors are addressed through careful sample selection and the inclusion of fixed effects to account for heterogeneity across products, time, and store formats.

Multichannel Retailing (Study 3)

The third empirical study is set in the context of multichannel grocery retailing, focusing on how consumer purchasing behavior evolves following the introduction of an online shopping channel. This setting provides a quasi-experiment[2] to examine long-term shifts in behavior among customers who adopt (i.e., start using) the new channel, particularly whether online channel adoption leads to incremental revenue or simply redistributes spending across formats.

The data come from the loyalty program of a regional grocery retailer, covering a cover a four-year period from 2015 to 2018 including pre- and post-introduction of the online channel. The online channel was introduced in late 2015, and this retailer was the only grocery chain in the region offering such an option at the time. This exclusivity minimizes competitive interference and enhances the internal validity of observed behavioral changes.

The dataset includes customer-level purchase histories across all both online and offline purchases, allowing for precise tracking of when each customer began using the online channel and how their purchasing patterns changed over time. Each transaction contains information on date, product category, quantity, spending, and purchase channel.

To examine the effects of online channel adoption, the study leverages the panel structure of the loyalty data to track individual customers both before and after the online channel introduction. Customers who adopted the online channel are compared against those who never adopted it throughout the observation window. This structure allows for the separation of pre-existing differences from actual behavioral shifts following adoption, thereby mitigating potential endogeneity concerns. By observing both adopters and non-adopters over time, the study enables a more credible assessment of whether online adoption leads to sustained changes in purchasing behavior.

While the dataset offers a unique opportunity to study online channel adoption, several limitations should be noted. First, although the retailer was the sole provider of online grocery shopping at the time of online channel introduction, competing retailers began offering similar services toward the end of the observation period, which are not explicitly accounted for.

[2] Accoring to Goldfarb, Tucker and Wang (2022), "Quasi-experiment refers to the use of an experimental mode of analysis and interpretation to data sets where the data-generating process is not itself intentionally experimental (Campbell 1965). Instead, quasi-experimental research uses variation that occurs without experimental intervention but is nonetheless exogenous to the particular research setting."

Second, purchasing activity varies across customers, limiting the ability to model detailed temporal dynamics, such as behavioral changes after one, two, or three years of adoption. Finally, as the data reflect the early phase of adoption, the number of online users is relatively small and likely skewed toward early adopters, which may affect generalizability. Despite these limitations, the study design remains well-suited to assess whether and how online channel adoption alters long-term purchasing behavior. The loyalty-based tracking, clean introduction window, and availability of a stable comparison group strengthen the internal validity of the findings, providing valuable insight into how digital channel strategies can affect customer value over time.

Digital Platforms (Study 4)

The final empirical context involves digital platforms, environments where consumer engagement and stakeholder visibility can be primarily influenced by platform's design mechanisms such as algorithms and editorial decisions. These systems determine what users see and engage with, thus influencing which stakeholders gain attention, traffic, or revenue. In such environments, potential external disruptions like the COVID-19 pandemic can alter user behavior at scale, raising questions about how platform exposure and stakeholder outcomes shift after that.

To examine this, the fourth empirical study investigates playlist follower dynamics on Spotify, which is a leading music streaming platform globally. The study focuses on how weekly follower growth for playlists varied before and after the pandemic, and whether these changes differed by relevant stakeholders. The dataset combines two primary sources. First, playlist-level follower data were obtained from *Chartmetric*, a commercial analytics provider that aggregates historical data from Spotify's Web API. This dataset includes weekly follower counts, curator type (e.g., Spotify-owned, label-affiliated, or independent), and content features such as the share of tracks from major labels and average track popularity. Second, data from *EveryNoise.com* are used to identify weekly instances of playlists featured on that platform, which is equivalent to platform-driven promotion that increases visibility. By integrating this information, the analysis distinguishes between follower growth arising from organic engagement versus algorithmically amplified exposure.

The final sample consists of 39,918 active playlists with 49 consecutive weeks of data spanning October 2019 to October 2020. This period covers both the pre- and post-pandemic declaration periods, allowing the study to assess whether and how a the pandemic changes engagement patterns across different curator types and content structures. The starting dataset from Chartmetric included over 1.2 million playlists. From this, playlists were filtered in stages: first, only those with sufficient data continuity were retained, and those lacking key variables, such as curator type, genre, or content attributes, were excluded. The resulting dataset provides an appropriate panel structure for modeling playlist-level follower changes in response to the pandemic.

While this context differs from traditional retail, the underlying mechanisms are highly comparable. In both settings, visibility is influenced by platform design, whether through shelf placement in physical stores or algorithmic curation online. Similarly, stakeholder outcomes depend not only on the quality of their offering but also on how consumers are exposed to and engage with those offerings. In this sense, playlist follower dynamics offer a relevant analogue to product visibility and customer engagement in retail environments, especially in the online environment.

The dataset is not free from limitations. It captures publicly observable playlist-level metrics, such as follower counts, rather than individual user behavior, limiting insights into the micro-level drivers of engagement. The influence of Spotify's algorithmic or editorial decisions is not directly observable and must be inferred from the featuring data. Additionally, follower growth serves as a proxy for engagement but does not capture actual listening behavior or financial outcomes. Nonetheless, the available sample provides a strong basis for detecting aggregate shifts in visibility across curator types and content structures, offering valuable insights for understanding how platform exposure and stakeholder outcomes shift after the pandemic.

4.2 Empirical Modelling Approaches

This section outlines the modelling approaches used to quantify how strategic retail decisions translate into performance outcomes across the four empirical studies. While the empirical data contexts vary, ranging from physical store purchases to digital platform engagement, the common objective is to isolate the impacts of retailer actions observable consumer responses.

The modelling approaches are presented in into three parts, based on the empirical context and the level of consumer behavior aggregation linked to performance outcomes:

(1) Modelling Retail Performance Using Aggregate Sales Data

(2) Modelling Retail Performance Using Individual Purchase Behavior

(3) Modelling Engagement Outcomes on Digital Platforms

<u>Modelling Retail Performance Using Aggregate Sales Data</u>

The first two empirical studies use aggregate sales data to evaluate how pricing strategies influence retail performance across physical store formats. The unit of analysis is brand-week level, aggregated from transaction data, allowing the studies to quantify market-level consumer response without relying on individual-level behavioral tracking. This approach is especially suitable for retailer-facing questions, such as whether specific pricing strategies improve sales or profitability across different retail formats.

In the first study, the focus is on profit-oriented evaluation of regular price setting for multitier private labels (PLs). The modelling follows a multi-step regression framework. First, price elasticities are estimated for each PL tier and format using observed variation in regular prices over time. These elasticity estimates are then combined with cost and price data to calculate contribution margins and profit effects. This two-part approach enables direct assessment of which tier–format combinations are most profitable, offering actionable insights for PL portfolio management (Geyskens et al., 2010; Gielens, 2012; ter Braak et al., 2013; Keller et al., 2020).

In the second study, the focus shifts to how reference prices and discount framing affect sales across store formats. The study uses a two-stage regression design: the first stage estimates brand-level sales responsiveness to regular prices and promotions, while the second stage tests how these elasticities are moderated by brand characteristics, category type, and store format. This allows for identification of conditions under which either regular price changes or promotional discounts are more effective (Haans & Gijsbrechts, 2011; Pauwels et al., 2007; Datta et al., 2022).

Both studies apply a sales-response modeling framework (e.g., Pauwels et al., 2007), capturing how changes in price influence weekly sales volumes. In particular, they adopt an error-correction specification, which disentangles short-term (immediate) effects from long-run adjustments toward equilibrium. This structure examines how consumers react to price changes across time, especially in a multiformat setting where regular prices, discounts, and brand presence may vary from week to week. To mitigate endogeneity concerns, both models incorporate a set of control variables and fixed effects. These include brand fixed effects, time dummies, and category-level controls that help account for unobserved factors such as brand popularity, demand seasonality, or promotional cycles (Datta et al., 2022).

This modeling strategy offers several advantages. First, it mirrors managerial practice, where performance metrics like sales and margins are typically monitored at the weekly brand or/and category level (Widdecke et al., 2023). Second, by aggregating across customers, the models avoid the need for individual-level tracking, which is often unavailable in practice, while still revealing meaningful market-level behavioral responses. Third, the multi-step and multi-stage design enables a clear separation between estimating price sensitivity and translating those effects into strategic insights about pricing, promotions, and profitability across brands, categories and formats.

However, the approach has some limitations. Most notably, the aggregate structure cannot capture within-brand heterogeneity in consumer responses. For example, how different shopper segments may react differently to the same promotion (Ailawadi & Harlam, 2004; Geyskens et al., 2010). Furthermore, observed price variation is not randomly assigned and may reflect broader retailer strategy, requiring caution in interpreting causal claims (Datta et al., 2022; Bijmolt et al., 2005). Still, by focusing on consistently available products across multiple store formats and using robust estimation techniques, the studies offer reliable insights into how pricing strategies translate into retail performance.

Modelling Retail Performance Using Individual Purchase Behavior

The third empirical study uses individual-level panel data to examine how online channel adoption affects customer purchasing behavior over time. This approach enables the analysis of behavioral shifts at the customer level, which is particularly useful for identifying how online channel strategies influence category spending, trip frequency, and overall customer value.

By observing a panel of customers across a multi-year window, covering both before and after the introduction of the online channel, the study captures longitudinal changes in behavior that follow the introduction and adoption of this new shopping format (Bilgicer et al., 2015; Avery et al., 2012). To isolate the effect of online channel adoption, the study adopts a difference-in-differences (DiD) framework, comparing changes in purchasing behavior between customers who adopted the online channel and those who did not. This quasi-experimental approach allows the model to distinguish between behavioral changes caused by adoption versus those driven by general time trends or unobserved consumer characteristics (Li et al., 2015). Propensity score matching (PSM) is used prior to the DiD analysis to construct comparable treatment and control groups based on pre-adoption shopping patterns, product preferences, and purchase frequency (Boehm, 2008; Campo & Breugelmans, 2015). Customer purchasing behaviors are modeled separately between short-term and long-term time frame.

This modeling strategy offers several advantages. First, it allows for customer-level inference, capturing the heterogeneity in how individuals respond to additional format adoption (Kushwaha & Shankar, 2013). Second, the panel structure enables robust within-customer comparisons, reducing bias from unobserved time-invariant traits such as household size or income (Konuş et al., 2008). Third, the combination of PSM and (DiD) mitigate self-selection bias by ensuring that adopters and non-adopters are comparable based on observable characteristics before the channel was introduced (Li et al., 2015), while DiD controls for time-invariant unobservables and shared temporal trends.

Nonetheless, the approach faces some restrictions and limitations. First, DiD relies on the parallel trends assumption, that in the absence of treatment, adopters and non-adopters would have followed similar trajectories over time (Li., 2023). While matching helps improve group comparability, this assumption cannot be directly tested and may become less plausible as the post-adoption period extends. Second, although the inclusion of covariates such as diaper purchases and store distance helps reduce confounding, these are relatively crude proxies for deeper household demographics and may not fully capture life cycle, income, or attitudinal differences that could influence both adoption and outcomes. Finally, DiD is less effective when treatment timing varies across individuals or when adoption reflects structural changes in consumer behavior that evolve gradually rather than in discrete shifts (Roth et al., 2023). Despite these limitations, the combined use of matching and DiD remains a transparent and theoretically grounded strategy for isolating the effects of voluntary channel adoption in a real-world retail setting. It enables a directional and practically meaningful interpretation of how online adoption affects long-term customer behavior, while acknowledging potential estimation boundaries.

Modelling Engagement Outcomes on Digital Platforms

The fourth empirical study examines digital platform engagement using playlist-level panel data from Spotify, focusing on how stakeholder exposures changes in response to the COVID-19 pandemic. This context differs from traditional retail but retains core analytical parallels, as engagement outcomes (e.g., follower growth) are affected by both consumer behavior and platform-driven mechanisms such as editorial curation and algorithmic promotion.

The unit of analysis is the playlist-week, enabling the measurement of weekly follower change as a proxy for aggregate user engagement. The study employs a fixed-effects panel regression model to isolate the effects of pandemic-related disruptions on follower growth, while controlling for time-invariant playlist characteristics and temporal fluctuations (Papies et al., 2022). Key independent variables include playlist curator type, content composition, and weekly indicators of platform-driven promotion (i.e., Search Page featuring). This approach allows the analysis to detect engagement shifts attributable to platform and content features rather than inherent playlist characteristics.

This modelling strategy offers several advantages. First, the playlist-level panel allows for detailed tracking of engagement changes across a broad sample of Spotify playlists. Second, the fixed-effects specification accounts for unobserved heterogeneity at the playlist level, such as theme, brand strength, or historical growth patterns, which supports more credible within-playlist comparisons over time. Third, the inclusion of week fixed effects helps control for seasonality and platform-wide shifts in user activity, while the continuous tracking of the same playlists before and after the pandemic allows comparisons across comparable calendar periods. This structure ensures that any observed changes in follower growth are more likely attributable to pandemic-related disruptions rather than seasonal patterns or content release cycles.

However, the approach is subject to certain limitations. First, the fixed-effects model might better suited for detecting large, persistent changes in engagement rather than subtle or short-lived shifts. As such, smaller effects, particularly those limited to a subset of playlists or time periods, may be harder to detect and subject to attenuation. In addition, any unobserved time-varying shocks that affect playlists differently may not be fully captured by the model structure, even with week fixed effects. Despite these constraints, the modelling strategy still provide a robust basis for detecting aggregate shifts in platform engagement and stakeholder exposure, especially in response to large-scale, externally induced disruptions like the pandemic (Sim et al., 2022; Denk et al., 2022).

5 Empirical Studies

This chapter presents the four empirical studies that collectively address the core research problem outlined in Chapter 2: how strategic decisions including setting price, adjusting regular price or offering promotions, introducing online channel and customer engagement, can be evaluated through the lens of consumer behavior using empirical data. Each study responds to a specific empirical challenge, applying the theoretical lens introduced in Chapter 3 and the data and methods described in Chapter 4.

The studies are situated in three distinct empirical contexts: physical multiformat retailing, multichannel retailing, and digital platforms. They examine how consumer responses vary by format, channel, and platform conditions, and how these responses translate into performance metrics such as sales, profitability, category revenue, and engagement.

Each subsection in this chapter corresponds to one of the four empirical studies:

- Study 1 quantifies the impact of prices across private label tiers and store formats.
- Study 2 evaluates how regular prices and promotional discounts perform under different brand, category, and physical store formats.
- Study 3 investigates the long-term effects of online channel adoption on customer behavior and retailer revenue.
- Study 4 explores how playlist follower growth on Spotify changed during the COVID-19 pandemic, with a focus on curator type, content characteristics, and platform exposure.

Together, these studies contribute to a deeper understanding of how strategic retail decisions can be empirically evaluated by examining the behavioral mechanisms through which they affect performance outcomes. While each study targets a specific decision and context, they collectively illustrate how data-driven approaches, devised under consumer behavior theoretical framework, can be used to assess the effectiveness of strategies across formats, channels, and digital platforms. The following sections detail each study's motivation, empirical design, key findings, and contributions.

5.1 Study 1

From Price to Profit: Multi-Tier Private Label Response Across Retail Formats

Author: Tanetpong Choungrayoon (Stockholm School of Economics)

Status: Work-in-Progress

Retailers increasingly use private labels (PLs) not just to improve margins but to position themselves strategically across store formats. Multi-tier PL strategies—offering budget, standard, and premium tiers—are designed to address diverse consumer preferences and reinforce store identity. However, how these tiers perform in terms of pricing responsiveness and profitability may vary significantly by store format, particularly in multiformat retail environments. This study investigates how PL price elasticity and profit outcomes differ across hypermarkets, supermarkets, and convenience stores.

While prior literature has documented the general rise of PLs and the benefits of tiered strategies (e.g., Geyskens et al., 2010; Ailawadi et al., 2008), there is limited empirical evidence on how these strategies play out across formats that differ in assortment depth, store missions, and customer expectations. Pricing moves that are effective in one format may underperform—or even backfire—in another. This study addresses this gap by quantifying format-specific responses to price changes across PL tiers and translating those responses into profit impacts.

The empirical setting is based on scanner panel data drawn from the retailer's loyalty membership database, covering transactions between January 2014 and November 2016. The dataset tracks shopping behavior of customers whose first recorded purchase occurred in the retailer's hypermarket. To ensure comparability, the product selection focuses on private label items purchased at least once every two weeks across the observation period (2014–2016). National brands with similar descriptions are included to benchmark competitive context. Five categories are retained—biscuits, canned vegetables, cereals, pasta, and dried fruits/nuts—with each offering multiple PL tiers across two or more formats. Assortment differences across formats are pronounced: while the hypermarket and supermarket carry most PL tiers, the convenience store typically features only the budget and standard tiers. In total, the analysis includes 135,776 shopping trips across 4,921 customers.

To analyze the effectiveness of PL pricing across tiers and formats, the study employs a two-stage modeling framework that explicitly imposes a structured interdependence among PL tiers. Firstly, a sales-response model is estimated using an error-correction specification that includes both own-price and cross-price effects across PL tiers. This structure allows the model to capture within-category substitution and cannibalization effects that arise when price changes in one tier (e.g., value-tier) influence the sales of another (e.g., premium-tier). These short-run elasticities are normalized to enable comparison across categories and formats, and are used to simulate expected changes in sales volumes under different pricing conditions.

Secondly, a profits-response model is estimated, also in error-correction form. The model incorporates predicted changes in sales—derived from the sales-response model—as key inputs, linking quantity adjustments back to pricing decisions. This step allows the estimation of format-and tier-specific profit elasticities, reflecting how price changes translate into bottom-line outcomes under real-world cannibalization and substitution dynamics. Both models include controls for seasonality, store-week effects, and endogeneity (via Gaussian copula terms), ensuring robustness of the estimates.

The findings reveal three key insights. First, consumer price responsiveness varies significantly across formats, even for the same PL tier and category. Second, cross-tier pricing effects are nontrivial—discounting a value-tier product may boost volume for that tier but reduce sales in adjacent tiers, especially in formats with constrained assortments. Third, profitability outcomes are highly format-contingent. While premium PLs tend to be less elastic overall, their margin benefits depend on format-specific volume dynamics and price sensitivity.

5.2 Study 2

Discount Offered Across Store Formats: Do store formats matter?

Author: Tanetpong Choungrayoon (Stockholm School of Economics), Rickard Sandberg (Stockholm School of Economics), and Sara Rosengren (Stockholm School of Economics)

Status: Work-in-Progress

Retailers frequently rely on two key pricing levers to drive sales: adjustments to regular prices and the use of promotional discounts. While both tools can influence consumer behavior, they are not equivalent in either perception or outcome. This study examines how regular price reductions and promotional discounts differentially affect sales across retail formats—hypermarkets, supermarkets, and convenience stores—within the same grocery chain. The analysis builds on the idea that shopping missions and consumer expectations vary across formats, leading to diverging responses to price cues.

Existing literature has highlighted the psychological distinctions between regular and promotional prices (e.g., DelVecchio et al., 2006; Hardie et al., 1993). While prior research has explored how consumers respond to price changes, fewer studies have empirically disentangled the effects of regular price reductions and promotional discounts across different store formats within the same retail chain. This study leverages an important feature of the empirical setting: retailers have more autonomy in setting regular prices but not promotions, allowing for natural variation in pricing strategies across formats.

The analysis is based on over 230,000 shopping trips made by 5,384 customers between 2014 and 2016, capturing detailed purchase behavior across 14 frequently bought product categories and 55 focal brands. The data come from a Nordic grocery retailer and are drawn from three stores—one representing each format—located in the same geographic area to minimize demographic and regional variation. Products and brands are selected based on consistency of purchase across formats and time, allowing for reliable cross-format comparison of price responsiveness. Categories range from commodities like milk and pasta to more discretionary items like chocolate and toiletries, enabling investigation of both format-level effects and category-specific dynamics.

The first stage of the analysis estimates brand-level sales-response elasticities for regular prices and discounts using a variant of the model proposed by Pauwels et al. (2007), with key controls for category traffic and trip types (major, fill-in, unplanned). These controls help account for the fact that shopping behavior is inherently different across formats—e.g., customers visit convenience stores more often for small, urgent purchases. The second stage regresses the estimated elasticities on brand- and category-level attributes, such as discount frequency, discount depth, private label status, storability, and category competitiveness, to examine which characteristics explain variation in price and discount effectiveness across formats.

The findings reveal three key insights. First, regular prices and discounts affect sales in systematically different ways across formats. Discounts tend to be more effective in hypermarkets and supermarkets, while regular price sensitivity is more pronounced in convenience stores—where fewer promotions occur and prices are often interpreted as signals of convenience value. Second, product characteristics matter: categories that are storable or impulsive exhibit higher discount sensitivity, while brands with deeper and more frequent promotions tend to experience greater discount elasticity. Third, private labels show distinct patterns in how they respond to price cues, depending on format and positioning.

5.3 Study 3

The Long-Term Effects of Online Channel Adoption in Grocery Retailing: A Research Note

Author: Tanetpong Choungrayoon (Stockholm School of Economics), Emelie Fröberg (Stockholm School of Economics), and Sara Rosengren (Stockholm School of Economics)

Status:

The introduction of digital channels has reshaped the grocery retail landscape, offering consumers greater flexibility while posing new strategic challenges for retailers. While many studies have explored who adopts online shopping and why, fewer have examined what happens after adoption—especially over an extended period. This study focuses on the long-term behavioral and financial consequences of introducing an online grocery channel, using large-scale transaction data from a Nordic grocery chain that added an e-commerce option to its existing physical store format.

The retailer launched its online channel in late 2015, offering home delivery to customers already served by its physical stores. This setting provides a unique opportunity to study how digital access complements—or substitutes—existing shopping behaviors. The research asks: Do customers who adopt online grocery shopping spend more overall? Do they shift their product mix toward more convenient or bulk purchases? And does adoption generate lasting value, or merely reallocate spending?

To answer these questions, the study applies a difference-in-differences (DiD) design combined with propensity score matching to compare customer behavior before and after online channel adoption. The data come from loyalty card transactions at a single hypermarket in a mid-sized Nordic city, covering two time periods: October 2014–November 2016 and August 2017–July 2019. The analysis focuses on 578 households that shopped regularly prior to the introduction of the online channel in October 2015. Among them, 147 adopted the channel within seven weeks of its launch and were matched with non-adopting households based on pre-adoption purchasing behavior. In total, the dataset includes over 116,000 receipts and 1.75 million product-level transactions, enabling a robust comparison of long-term spending, basket composition, and shopping patterns between adopters and their matched counterparts.

The results show that while the short-term effects of adoption are relatively modest, the long-term impacts are more pronounced. Online adopters increase their spending in categories that are heavy or bulky (e.g., pet food, bottled water) and reduce purchases in impulse-driven or high-effort categories like fresh vegetables and perishable snacks. The frequency of shopping trips does not increase substantially, but average basket size grows, leading to higher customer value over time. Importantly, this effect is not driven by promotional incentives or external shocks, but by structural changes in consumer behavior enabled by channel access.

These findings highlight the importance of looking beyond initial adoption metrics to understand the full implications of digital transformation in retail. For retailers, the shift is not just about adding a new touchpoint—it involves long-term changes in customer composition, product mix, and revenue dynamics. The study offers actionable insights into how digital investments can enhance customer lifetime value and supports more strategic planning around multichannel integration.

5.4 Study 4

How did Covid-19 Affected Playlist Followers on Spotify

Author: Tanetpong Choungrayoon (Stockholm School of Economics), Hannes Datta (Tilburg University), and Max Pacheli (Tilburg University)

Status:

The COVID-19 pandemic reshaped how music was consumed and discovered, especially on digital platforms where playlists play a central role in surfacing content. This study investigates how follower dynamics on Spotify playlists changed during the pandemic, with a focus on curator identity, playlist popularity, and the share of major label content. By examining which types of playlists gained or lost traction, we provide insights into how visibility and potential revenue opportunities shifted across stakeholders in a time of disruption.

To conduct this analysis, we compiled weekly panel data on over 39,000 active Spotify playlists from October 2019 to October 2020, capturing 19 weeks before and 30 weeks after the WHO's pandemic declaration on March 11, 2020. The follower data comes from *Chartmetric.com*, while weekly Search Page featuring data is sourced from *Everynoise.com*. Playlists in the sample span a wide range of curator types—Spotify, major labels, independent labels, artists, professional curators, and users—and vary in both follower size and track composition. We control for visibility boosts via platform promotion (i.e., Search Page features), playlist themes, and seasonality to isolate the effects of the pandemic from other confounding factors.

The empirical strategy employs a unit fixed-effects model to estimate how playlist followers changed before and after the pandemic onset, focusing on within-playlist variation. This allows us to control for persistent playlist characteristics (e.g., genre, theme, long-run popularity) while measuring the effect of time-varying factors like pandemic-related restrictions and shifts in mobility. Three different pandemic indicators are used: a binary post-pandemic declaration indicator, a country-weighted government Stringency Index, and country-weighted changes in residential mobility from Google. This combination helps us capture both the immediate and evolving effects of the pandemic on digital engagement.

We also examine heterogeneous effects across playlist subgroups. Playlists are categorized into five tiers based on their popularity percentile (e.g., top 0.1%, 0.1–1%, 1–5%, etc.), allowing us to assess whether superstar, mid-tail, or long-tail playlists were more resilient. We then investigate how curator type shaped engagement trends, asking whether well-resourced curators (e.g., Spotify, major labels) fared better than independent ones. Lastly, we analyze whether playlists with a higher share of major label content saw different follower dynamics during the crisis.

The results show a non-uniform impact of the pandemic on follower growth. Playlists curated by Spotify exhibited notable resilience and even growth in the mid- and long-tail range, suggesting that platform-curated content benefited from embedded visibility mechanisms like algorithmic promotion and prominent positioning. In contrast, playlists curated by major labels saw mixed results—while some superstar playlists maintained followers, growth flattened or declined over time. Surprisingly, a higher share of major label tracks did not consistently translate into greater follower gains. Once we account for individual track popularity, the advantage of major label presence diminishes, suggesting that audiences responded more to song-level appeal than label affiliation.

These findings suggest that the crisis created openings for new or less visible curators and content types to gain traction, especially as listeners explored a wider variety of content under stay-at-home conditions. They also highlight the strategic importance of curation visibility and algorithmic reach in driving platform engagement during disruption. For music industry stakeholders—and by extension, digital retailers—the findings reinforce the value of adaptive content strategies, diversified engagement tools, and resilience planning for uncertain times.

6 Discussion and Future Directions

In this final chapter, I step back from the specifics of each study to reflect on what the thesis contributes more broadly. The sections that follow are organized around five dimensions: theoretical contributions, managerial implications, methodological notes, reflections from the research process, and limitations with directions for future research. Each section connects the dots across the empirical chapters, drawing out patterns and lessons that may not be immediately visible in isolation. In doing so, this chapter aims to offer both a synthesis of what has been learned and a foundation for where the conversation might go next.

6.1 Theoretical Contributions

This thesis contributes to marketing and retail theory by demonstrating how large-scale behavioral data, when analyzed through the lens of established theoretical frameworks, can yield new insights into the effectiveness of strategic decisions, including pricing, channel introduction, and digital platform engagement, across different retail settings. By systematically linking data-driven empirical analysis with consumer behavior theory, the four empirical studies collectively clarify how context, action, and consumer response jointly shape performance in modern retail and platform environments.

First, this thesis strengthens the understanding that retail context is fundamental for assessing the effectiveness of strategic decisions. Across Studies 1–4, evidence demonstrates that pricing sensitivity, price-promotion outcomes, and engagement levels are not consistent across formats, brands, channels, or stakeholders. Studies 1 and 2 show that the impact of pricing strategies and discounts for private label products cannot be generalized even within the same retailer; price elasticities and profit outcomes differ systematically by store format, private label tier, and product category. These findings provide direct, retailer-level evidence in line with recent multiformat and private label research (e.g., Haans & Gijsbrechts, 2011; Geyskens et al., 2010), as well as broader discussions on marketing-mix customization and fragmentation across formats and markets (Wichmann et al., 2021), and further demonstrate that performance measurement must move beyond aggregated effects to account for the combined influences of context, brand, and assortment. Study 4 extends this context principle to digital platform environments, revealing that playlist engagement and stakeholder visibility on Spotify shifted distinctly by curator type (e.g., Spotify, major labels, independents) and content composition during the pandemic, rather than following uniform patterns across the platform.

Second, the studies show that consumer behavior is central to understanding how retailer actions ultimately influence measurable performance. Rather than presenting outcomes without explanation, each study uses empirical models grounded in consumer behavior literature to connect pricing, channel, and platform actions to observed purchasing, engagement, and revenue effects. For example, Study 3 draws on the logic of shopping utility maximization to explain why online channel introduction for groceries altered the mix and monetary value of purchases over multiple years, even as shopping frequency remained stable. The study expands on work by Campo & Breugelmans (2015) and Melis et al. (2016) and aligns with recent evidence on household adaptation to economic pressures and category-level adjustments (Scholdra et al., 2022), by demonstrating that long-term revenue changes are due to persistent shifts in the types of categories shopped, notably with increased value per visit in categories with high online delivery convenience. Meanwhile, Study 4 shows that consumer engagement with playlists tracked macro shifts in mobility and daily routine during COVID-19, with user exploration favoring mid- and long-tail playlists when time at home increased, an effect that would not be visible absent a behavioral lens.

Third, the thesis qualifies and refines existing knowledge on the effectiveness of classical pricing and channel strategies. Through detailed comparison of regular price changes, temporary discounts, and tiered private label approaches in Studies 1 and 2, findings show that neither price nor discount elasticity is consistent across products or store types. For instance, discount responsiveness is higher for private labels in hypermarkets, while in supermarkets, standard and premium tiers generate more profit despite less elastic demand. These results not only build on previous findings (e.g., Shankar & Krishnamurthi, 1996; Ailawadi et al., 2006; Widdecke et al., 2023) but also clarify how interaction effects between format and assortment structure define when each pricing tool is most effective and where potential gains may be realized. Study 3 similarly clarifies that online channel effects on long-term value are not additive but depend on persistent behavioral change in specific categories and on the composition of each customer's shopping trips.

Fourth, this thesis extends existing theory by showing how external shocks can reshape competitive dynamics and stakeholder engagement across both digital platforms and traditional retail settings. Established literature on product harm crises in retail demonstrates that sudden disruptions, such as recalls or safety incidents, can shift consumer attention, alter brand perceptions, and create both risks and opportunities for incumbents and niche players alike (Dawar & Pillutla, 2000; Cleeren et al., 2017; Giese et al., 2014). Leading brands may recover or even strengthen their position through effective crisis response, but such events often prompt consumers to explore alternatives, redistributing market attention at least temporarily. Study 4 offers a parallel from the digital environment: during the COVID-19 pandemic, as consumer routines were disrupted, engagement on Spotify playlists did not simply reinforce the dominance of established "superstar" stakeholders. Instead, follower growth broadened toward mid- and long-tail playlists, just as product harm events sometimes shift retail attention to less prominent brands. These insights reflects broader platformization dynamics that reallocate brand power and stakeholder control (Wichmann et al., 2023), and contextualize platform findings alongside classic retail responses to crisis. They emphasize that the performance of brands or stakeholders under disruption reflects the interplay between initial position, organizational response, channel design, and adaptive consumer behavior.

Finally, the thesis demonstrates the necessity, but also the limitations, of data-driven and analytics-based approaches for strategic retail evaluation. By leveraging unique retailer and platform datasets that directly connect strategy to real consumer decisions, these studies illustrate that actionable insights come not from sheer data scale, but from integrating context-specific theoretical interpretation and careful empirical modeling. Performance generalizations such as "discounting increases sales" or "online channels are always profitable" are shown to be conditional on retail and consumer context. The thesis thereby substantiates calls for theory-driven, context-aware analytics (Dekimpe, 2020), , echoing similar arguments for more adaptive, context-specific marketing-mix decisions in dynamic retail environments (Wichmann et al., 2021), providing a model for future research that balances explanation with prediction.

In summary, this thesis integrates empirical strategies and behavioral theory to clarify when, where, and how strategic retail and platform decisions yield results, and under what circumstances effects are likely to be observed. The findings support a shift from search for universal rules to a more precise, context-sensitive understanding, guiding both academic theorizing and practical management in modern retail environments.

6.2 Managerial Implications

Some of the findings in this thesis may appear, at first glance, to be rather obvious. Price and discounting are not the same thing. Store formats influence how consumers behave. Platforms benefit from asymmetric structures that privilege their own content. None of this is likely to surprise experienced retail managers. Yet there remains a significant gap between what is commonly acknowledged and what is consistently operationalized. In practice, prices and promotions are often aggregated in performance reports under a single "pricing" obscuring their distinct effects (McKinsey & Company, 2021; RELEX Solutions, 2023). Store formats may be treated primarily as different offering channel rather than as distinct behavioral contexts with unique consumer patterns (Bain & Company, 2021; Accenture, 2023). The value of this thesis lies not in revealing hidden secrets or mechanisms but in converting the familiar into something actionable by quantifying effects, testing them across contexts, and exposing where common intuition fails to scale. Strategic ideas that appear sound in isolated anecdotes or short-term pilots often produce diminishing or even counterproductive results when extended across store formats, product categories, or customer segments. By tracing these effects systematically, the studies show where conventional practical knowledge can mislead when applied too broadly or without regard for context and temporal variation. and exposing where common intuition fails to scale. This is in line with research showing that managerial relevance increases when insights are generated from real-world observations and explicitly lead to practical feasibility (Schauerte et al., 2020).

Take, for instance, the idea that deep discounts drive sales. Of course they do. But in what format, for which type of brands (or which tiers in private labels), and for how long? Studies 1 and 2 show that profit gains from price increases on budget private labels hold in hypermarkets, but not in supermarkets. Likewise, promotion fatigue may be applied for some categories but not others, and past exposure to discounts dampens future effectiveness. These are not revolutionary insights but they are rarely specified this clearly. By showing that the same tactic works differently by format, tier, and promotional history, the studies offer practical boundaries for when promotional tactics can be intensified and when they risk doing more harm than good. The lesson is not "discounts work" or "formats matter," but that treating all customers, categories, and channels the same is not just lazy, it's expensive.

Rather than offering the kind of broad, generic advice often found in industry reports ("be agile," "embrace personalization," "build resilience") (e.g., Deloitte, 2023; McKinsey & Company, 2022; Accenture, 2023), this thesis provides evidence-based distinctions that clarify where strategy actually matters. It does not call for reinventing retail, but shows where practical adjustments, rooted in observed outcomes, can lead to meaningful gains. The methods are well-established, and the settings are everyday, not exceptional. But the findings are drawn from actual consumer behavior in real environments, tracked over time and across formats. The data are not without limitations, but the patterns are consistent. And the implication is straightforward: performance improvement does not require new tools so much as better use of the ones already available, with more precision, more structure, and closer attention to context.

This thesis also resists the industry temptation to assume that more data will fix everything. Retailers and platforms are already drowning in data; the real shortage is in interpretation. Throughout the studies, better understanding came not from bigger datasets, but from framing decisions through the lens of consumer theory, whether thinking in terms of utility, perceived value, or platform power structures. Theory, in this sense, is not an academic luxury but a practical investment. It offers a flexible conceptual thinking that travels across contexts and can help make sense of even noisy or partial data. Understanding customers, such as why they switch channels, how they react to price, and what draws them to content, is a far more transferable and scalable asset than a new dataset or tool. The point is not to reject data, but to realize that more data does not always mean better decisions.

One area where this thesis may offer a less commonly emphasized contribution is in its attention to time. In fast-moving commercial environments, the temporal dimension is often treated as an operational detail, useful for campaign calendars or short-term KPIs, but not central to strategic thinking. Yet across all four studies, it becomes clear that when effects unfold is just as important as what those effects are. Study 1 distinguishes between short- and long-run price responses; Study 3 tracks persistent shifts in purchase behavior following online channel adoption; and Study 4 captures how platform engagement patterns diverge in response to a system-wide disruption. These analyses move beyond abstract talk of "sustainability" to ask more measurable questions: What actually persists? For whom? And for how long? By treating time not as a reporting interval but as a dimension of strategic effect, the thesis encourages managers to think not just in outcomes but in trajectories, examining how decisions accumulate, attenuate, or reverse over time.

Finally, while the studies are grounded in grocery retail and music streaming, their implications travel well. The findings from multiformat pricing and channel shifts extend can be applied constructively to other frequently purchased product categories such as health, household goods, or personal care, where behavioral regularity and category-specific sensitivities also play a role. Similarly, the results from platform engagement apply not only to Spotify but to any retailer that curates digital visibility through search results, homepage banners, or recommendation algorithms. What matters is not the domain but the structure: the interaction between format, control, and consumer decision-making. These patterns are not industry-specific; they reflect mechanisms that recur whenever businesses manage visibility, pricing, and engagement across formats or channels.

In sum, this thesis does not pretend to offer a breakthrough managerial discovery. But it does suggest that many of the answers retail managers seek are already in their data, waiting to be unlocked not by bigger tools or louder slogans, but by clearer logic, better framing, and just a little more respect for the quiet power of variation over time.

6.3 Methodological Notes

~~This thesis does not introduce new methodological innovations. Rather, it applies established tools from marketing science and econometrics to real-world retail challenges, with the goal of producing insights that are both rigorous and relevant. The methods used, such as error correction models, quasi-experimental designs and fixed-effects panel models, are not ends~~

~~in themselves, but tools to better understand the strategic questions posed in each study. In that sense, statistics is not the story, but the lens through which the story becomes clearer.~~

Throughout the thesis, theory serves not just as background but as a guide in shaping the empirical approach. The choice of variables, model structures, and interpretive frameworks are all grounded in prior research, ensuring that the results speak to meaningful constructs in retail strategy and consumer behavior. In particular, each study connects theoretical ideas to measurable outcomes: from price elasticity to profit dynamics, from category utility to long-term revenue, from content visibility to follower engagement. These connections help translate statistical models into strategic implications.

A recurring methodological consideration across the studies is the use of panel data structures that support analysis of behavioral change over time. Such data structures are especially effective in capturing the variation and persistence of consumer behavior in response to marketing actions, offering detailed insights that go beyond static snapshots (van Heerde & Dekimpe, 2024). While modelling on panel data are often employed simply to control for unobserved differences between units and times, their role here is merely only for controlling. Panel data allows us to examine not just whether a strategic action has an effect, but how that effect may change over time. Since the research questions emphasize both immediate and longer-term responses to retail decisions, temporal dynamics are not just a technical detail but a part of the analysis. In Studies 1 and 2, error correction models separate short-term effects from longer-term adjustments in sales and profits (Pauwels t al., 2007). Study 3 uses a difference-in-differences design to track sustained behavioral changes after digital channel adoption, comparing pre- and post-periods between matched customer groups (Goldfarb et al., 2022). Study 4 applies a first-differencing strategy and time fixed effects to isolate change while accounting for shocks related to the COVID-19 pandemic. Across all studies, time is not just a background variable, it's a way to understand how consumer responses develop, persist, or fade, depending on the strategy and the setting. This reflects a broader recognition that "consumer attitudes and behaviors are fundamentally dynamic processes," and that capturing these changes is "crucial for truly understanding consumer behaviors and for firms to formulate appropriate actions" (Zhang & Chang, 2020).

Another essential part of the methodological approach is the careful use of available data, balancing its strengths while acknowledging its limitations. Across all studies, efforts were made to account for unobserved heterogeneity, control for confounding factors, and use robust estimation techniques. For example, the first study applies error correction models to estimate both short- and long-term price effects across private label tiers and formats, linking sales responses to profit outcomes. The second study uses a hierarchical regression design to isolate differential effects of regular pricing and discounts while accounting for brand- and category-level moderators. The third study employs a difference-in-differences design with propensity-score matching to estimate long-term behavioral changes following online channel adoption. And the fourth study uses a unit fixed-effects panel to assess changes in playlist followers over time, leveraging government restriction indices and mobility data to contextualize pandemic effects. These designs reflect the shared goal of extracting credible insights from observational data while respecting its boundaries. This also aligns with recent calls for an empirics-first approach, where theory generation is grounded in the systematic analysis of real-world behavioral data rather than imposed a priori (Golden et al. 2022).

What ties the empirical work together is the effort to link smaller behavioral responses, how a consumer reacts to a price, adopts a channel, or engages with a playlist, to broader retailer-level outcomes. This approach reflects the belief that meaningful analysis emerges not from statistical complexity alone, but from building bridges between components of a problem (Leeflang et al., 2014). For example, in the pricing studies, the analysis moves beyond elasticity to consider profit response and substitution across private label tiers. In the digital adoption study, the analysis goes from product mix shifts to sustained revenue differences. In the platform study, follower changes are used to infer visibility and stakeholder outcomes. These layered structures ensure that analysis stays connected to the broader questions of value creation, performance, and strategic adaptation.

Finally, by following a consistent logic; from theory, to model, to interpretation, the studies maintain coherence and comparability across domains. This structure allows for clearer synthesis across chapters, as discussed earlier in the theoretical and managerial sections. Using established methods thoughtfully, with clear theoretical grounding and real-world data, enhances not only the validity of each study but also their combined ability to inform decisions. The result is not just a collection of findings, but a set of interconnected insights that reflect how analysis can be practically and meaningfully applied.

6.4 Limitations and Future Directions

Like all empirical research, this thesis is shaped by constraints in data, scope, and method. Recognizing these limitations is not only important for framing the validity of the current findings but also important for guiding future research that builds on and improves them. While each study faces specific constraints, two broader themes run across the work: the conditional nature of the findings and the methodological boundaries of observational data analysis.

A common limitation across the studies is their context-specific nature. For instance, the analyses of pricing effectiveness and private label tiers are drawn from a single Nordic grocery retailer. While this offers rich, retailer-specific insights and avoids confounding chain-level variation(Geyskens et al. 2010; Gielens 2012), it also limits generalizability. Consumer preferences, competitive dynamics, and operational strategies may differ in other markets or retail systems. Moreover, shopper behavior under Nordic welfare structures, category mixes, and retail consolidation may differ from environments with different logistical, pricing, or loyalty norms. Future work could replicate and extend these analyses across different geographies or retailer types to explore how store format and private label architecture interact in broader environments (e.g., Gielens & Steenkamp 2019).

In the first and second studies, another limitation stems from the focus on pricing without incorporating other marketing mix variables such as promotion exposure, in-store displays, or advertising. Although the models isolate the effects of regular prices and discounts on sales and profits, they do not account for broader category dynamics or concurrent marketing efforts that might influence results (Bijmolt et al. 2005; Nijs et al. 2001). Further, the treatment of pricing as exogenous may not fully account for strategic managerial adjustment in response to demand feedback (Pauwels et al. 2007; Wedel & Kannan 2016). While the profit-based model adds richness beyond volume outcomes, it assumes margin constancy and does not incorporate inventory or supplier-side considerations. Future research could integrate more detailed cost data and multi-touch attribution to model profitability more holistically (Dekimpe & Hanssens 2020).

The third study, on online channel adoption, uses a quasi-experimental design with matched controls and difference-in-differences estimation to assess causal effects. However, as with all non-randomized designs, selection bias remains a concern, particularly with early adopters, who may have unobservable characteristics (e.g., risk tolerance, tech affinity) that affect their behavior (Goldfarb et al., 2022; Melis et al. 2016). While robustness checks with late adopters help mitigate this concern, future studies could improve internal validity through experimental designs, such as A/B testing or field experiments, when feasible (Li et al. 2015; Avery et al. 2012). Additionally, this study focuses on a specific category, which is groceries that hold its own delivery constraints and purchase rhythms. Future research could expand the framework to high-involvement or service-based categories, where channel adoption may follow different patterns (Kushwaha & Shankar 2013; Campo et al. 2020).

The fourth study, on platform engagement during the COVID-19 pandemic, leverages a rare external shock to assess curator-level outcomes on Spotify. While this design offers a clean identification strategy using within-playlist fixed effects and external variation in mobility restrictions, the timeframe is relatively short, limited to one year before and after the pandemic declaration. As such, it captures immediate behavioral shifts but cannot speak to long-term platform adaptation or stakeholder recovery. Further, the study focuses on playlist followers as a proxy for engagement, which, while correlated with streams, does not directly measure listenership or revenue redistribution (Pachali & Datta 2024). Future work could incorporate listening data, ad exposure, or royalty distributions to provide a clearer link between engagement patterns and financial outcomes.

Across all four studies, the reliance on observational data brings the typical trade-offs of real-world research: high external validity but limited causal precision. While efforts were made to triangulate results using model-free diagnostics, fixed effects, and robustness checks, the risk of omitted variable bias and endogeneity cannot be fully eliminated. Future research could push further by integrating survey data, field experiments, or simulations that allow for more granular theory testing and richer behavioral inference.

In sum, this thesis advances empirical knowledge across multiple domains, but it also makes clear that there is more to uncover. By embracing these limitations as open questions rather than weaknesses, future research can extend the narrative, both refining our theoretical understanding and improving the practical tools we use to navigate modern retail and platform landscapes.

7 Epilogue

The previous chapters have highlighted what this thesis contributes to theory, practice, and methodology. And honestly, I cannot help but feel a little strange writing about contributions to theory, retail management, and method as if they were separate boxes. To me[3], none of these insights came from pursuing one category in isolation. They are obtained from a process that was, let's be honest, messy, nonlinear, and definitely not the clean, post-hoc story you read in journal articles. This process was made up of cycles of understanding the data, recognizing limitations, building visual tools, and refining models, not as neat, sequential steps, but as overlapping and recursive loops. Messy as it was, that was where the most meaningful progress happened.

To make sense of anything, I first had to understand the data, not just statistically, but structurally and contextually. What does each variable represent? What patterns emerge without any models? What is missing, and why? These questions became the starting point for every project. And just as much as theory guides analysis, the data pushed back, often forcing me to revisit assumptions or rethink design choices. Over time, I learned to ask better questions, shifting from "Is this effect significant?" to "What does this tell us about how people behave, and how businesses respond?"

Throughout my studies, some of the most important insights did not come from rigorous models or perfect specifications. They came while exploring through dashboards (see example in Figure *1* andFigure *2*). No hypothesis tests, no coefficients, just time series, cohort comparisons, and a thousand tabs open at once. These tools were not just exploratory; they were epistemological in the sense that they shaped what I could even see as knowable or worth investigating[4]. They helped me understand what the data looked like before I tried to explain it; what changed, what didn't, and what simply refused to behave.

Over time, I came to realize that research is not just about technical proficiency or theoretical advancement. It is about learning to navigate contradictions: between theory and data, detail and direction, explanation and uncertainty. It's about knowing when to zoom in on a variable and when to ask if that variable even matters. In this sense, research became less a

[3] Which means no citation to be added.
[4] At least for those of us playing the positivist game, trying to falsify hypotheses, quantify behavior, and observe the world through patterns in data. If your goal is to interpret meaning, not measure movement, this epistemological tool may not be applied.

process of control and more a negotiation, with the data, with the literature, with my own assumptions.

And in that mess, the boundaries started to blur. Between theory and data. Between method and meaning. Even now, working in the industry, I find it strange how often we talk about "academia versus practice" as if they live on separate planets. But the process including the struggle to make sense of behavior, to predict outcomes (whether through behavioral explanations or algorithmic models), and to improve decisions, is nearly the same. The only real difference is emphasis. Academia sharpens its explanations until they are publishable. Industry sharpens its tools until they are profitable. One seeks to understand what's going on. The other, what to do next. But both chase relevance, just on different timelines.

That said, I can't resist a confession.

Sometimes I wonder if social science has become a full-blown circus of triviality. Everyone's performing, juggling regressions, walking the tightrope of robustness checks, and pulling "contributions" out of a hat. We spend years polishing results so safe, so painfully obvious, that any trace of genuine insight is lost under layers of statistical rigor. Then comes the best part: we feed the findings into Artificial Intelligence and ask, "What's the contribution?" As if the machine, not the mind, holds the key to meaning. The only real novelty? A new dataset, usually slightly bigger or slightly weirder than the last one. It is exhausting. We are rewarded for saying something new, not necessarily something true, and certainly not something useful. At times, I feel like we are just optimizing for clever footnotes on the margins of irrelevance.

But let's not pretend industry is not running its own sideshow. If academia is a circus of triviality, then industry might be a magic act, pulling quick solutions out of black-box algorithms, waving around KPIs like they are proof of wisdom, and vanishing ambiguity with a well-timed dashboard. It may speak the language of efficiency, but the spectacle is familiar. There is the same pressure to produce, the same glossing over of uncertainty, the same tendency to treat models as truths rather than tools. Different tent, same tricks, both optimizing for output, both falling into a familiar kind of instrumentalism.

And yet, I remain optimistic. Because the real value, I think, lies in the overlap. In realizing that research is not just about what practitioners can learn from us, but what we can learn from them. Industry does not need to be told that context matters because they live inside it. They do not theorize about heterogeneity because they market to it. And maybe, just maybe, the good research is not the kind that holds itself apart from practice, but the kind that builds from the same tools, the same constraints, the same messy dashboards that sparked every idea in this thesis.

If there's one mindset I take from this thesis process, it is this: judgment matters more than jargon. Rigor is necessary, but useless without relevance. And the real skill is not mastering the model, it is learning how to move between the model and the mess. That's where strategy lives. That's where insight happens. It's the PhD student who realizes a perfect p-value means little if the question doesn't matter. It's the retailer who knows that a dashboard spike means nothing until you understand which customers drove it and why. Models can calculate, but only judgment can interpret.

Figure 1 Dashboard example for exploring time-series of price across brands, categories and store formats

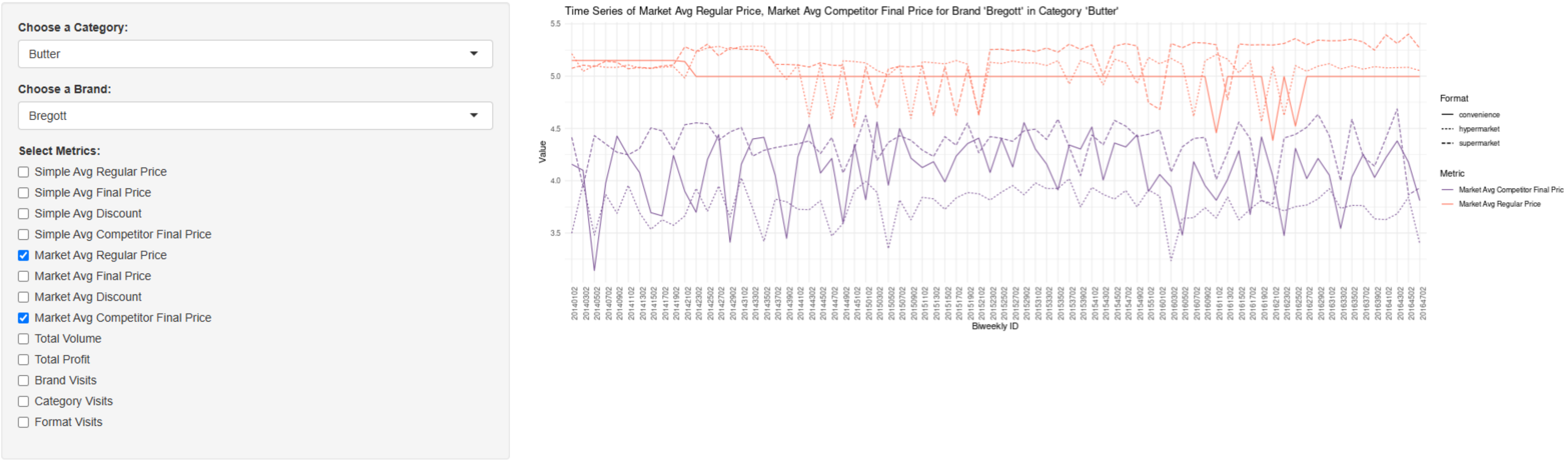
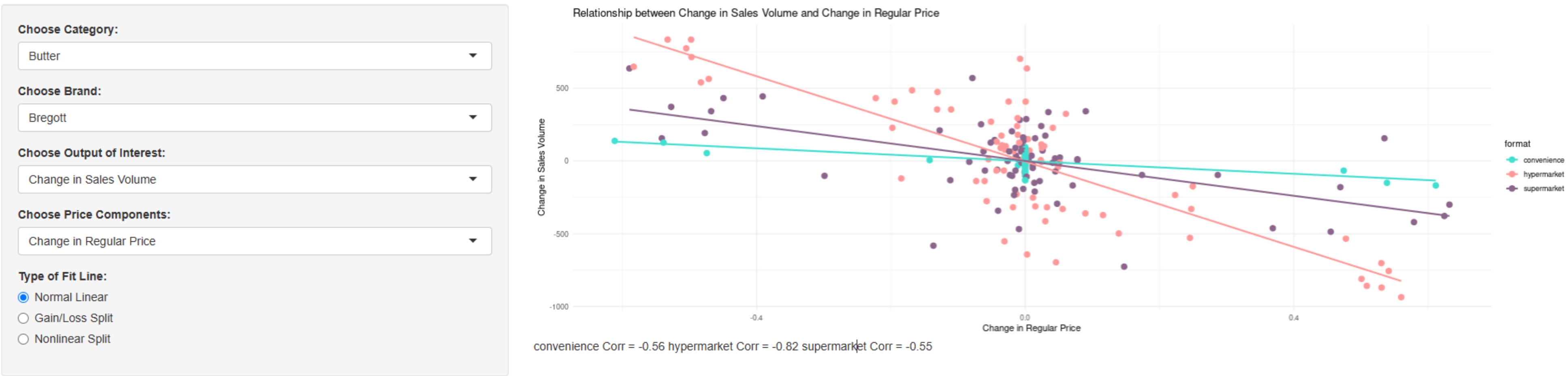


Figure 2 Dashboard example for exploring model free relationship between changes of prices and sales across formats



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