Tanetpong (Ned) Choungprayoon

MODELING RETAIL PERFORMANCE THROUGH CUSTOMER BEHAVIOR

EVIDENCE FROM MULTIFORMAT, MULTICHANNEL, AND PLATFORM SETTINGS

STOCKHOLM SCHOOL OF ECONOMICS

MODELING RETAIL PERFORMANCE THROUGH CUSTOMER BEHAVIOR

Retailers constantly face familiar questions: Why do discounts work better in some stores than others? How does adding an online channel change customer behavior? What happens on digital platforms when external shocks disrupt the market? While these questions may seem straightforward, the answers are often complex and context-dependent. Understanding not just what happens, but what drives these differences, is not always easy.

This thesis examines how retail strategies such as pricing decisions, channel expansion, and product visibility shape customer behavior and influence performance outcomes. Using large-scale data and empirical models across physical stores, online channels, and digital platforms, it shows how similar actions can lead to different results depending on context. The analysis combines theory with data to move beyond description and provide structured explanations of observed patterns.

The contribution is to show that retail performance depends on how customers respond to strategic decisions. By quantifying these responses across retail environments, the thesis links strategic decisions to performance outcomes by connecting empirical evidence with theoretical insights from customer behavior. It provides a structured way to interpret data and supports more consistent, evidence-based decision making in retail.

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To
My Family
And My Beloved Friends,
Both Those I Have Met and Those I Have Yet to Meet

Foreword

This volume is the result of a research project carried out at the Department of Marketing and Strategy at the Stockholm School of Economics (SSE).

This volume is submitted as a doctoral thesis at SSE. In keeping with the policies of SSE, the author has been entirely free to conduct and present his research in the manner of his choosing as an expression of his own ideas.

SSE is grateful for the financial support provided by Torsten Söderbergs Stiftelse, Ann-Margret och Bengt Fabian Svartz Stiftelse, and Hans Werthénfonden, which has made it possible to carry out the project.

Göran Lindqvist	*Hans Kjellberg*
Director of Research Stockholm School of Economics	Professor and Head of the Department of Marketing and Strategy

Preface

Let's be honest: chances are you're not going to read this entire thesis, and that's totally fine. You're probably here because this is the preface and it's the perfect place to begin (and perhaps to end). We are all busy, right? Academics are busy working on papers (publish or perish!), and practitioners are swamped with back-to-back meetings and projects. But stick with me for just this short preface.

Over the past five years, my PhD has kept me deeply interested in retail analytics. The questions I ask might sound familiar (as some might say, not particularly groundbreaking): Why do discounts work better in some stores than others? How does launching an online channel shift customer behavior?[1] What happens to customer behavior on digital platforms in the face of an external shock like COVID-19? These are questions that retailers, like consumers, ask all the time. What sets this work apart is my ability (and privilege) to spend half a decade or more exploring the 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, and I examine how customers respond in ways that impact sales, profits, and outcomes on digital platforms. 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

Choosing a price is one thing, but it is another thing to know how customers respond differently to that price depending on where they shop. In the first two of the studies presented herein, I examine how pricing affects customer behavior across different physical store formats including hypermarkets, supermarkets, and convenience stores. The first study looks at private label tiers. Including basic, standard, and premium tiers, it shows that sales and profit elasticity vary significantly depending on the store format. The second study compares regular price reductions with promotional price discount. It shows that the same price cut can produce different effects depending on the context.

[1]Throughout this thesis, the terms consumer and customer are used with distinct but related meanings. The term consumer refers to general consumer behavior, particularly the psychological and decision-making processes often examined in consumer behavior research. The main focus of this thesis is on customers, taken as individuals actively interacting with retailers within the studied empirical settings. In other words, this thesis draws on consumer theory to explain how retailers might expect their customers to respond to strategic actions.

2. Multichannel: The Long-Term Impact of Going Online

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 bottled water, and reduced purchases in impulse-driven or perishable items like snacks or 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: Customer Behavior During External Shocks

In the final study, I examine how customer behavior on digital platforms shifted during the COVID-19 pandemic. The study uses follower growth on Spotify playlists as an empirical example to capture changes in this digital platform context. The results show that playlists curated by the platform remained resilient, but those associated with major record labels and superstar tracks lost momentum. The takeaway addresses more than music. In algorithmic environments where attention is scarce, resilience comes from diversified offerings, mid-tail strategies, and institutional curation, not from a sole product's power or influence. For retailers operating on digital platforms, this highlights the importance (especially during periods of uncertainty) of visibility management and content strategy.

If you continue flipping through the pages of this thesis, you will come across theoretical discussions, mathematical notations, and statistical models. Such material 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 formulas as precision tools to quantify observations and draw conclusions. Don't worry; the theoretical discussions and equations are here to shed light on how retail strategies, in pricing and platforms, connect with customer behavior. It is like building a house, where theory provides the blueprint, data supplies the raw materials, and models are the tools that assemble everything into something meaningful and durable.

This thesis is not a definitive guide to retail strategy. What I offer is a series of observations, tests, and tentative conclusions grounded in empirical data. The value is not just in the answers but in the act of asking, of 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 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.

Acknowledgements

I have far more people to thank than these pages can reasonably accommodate. In fact, I could probably write another thesis just for that. But in the interest of keeping things readable, I will focus here on a few individuals and groups, while many others are acknowledged throughout without being named individually. If you are reading this, you will likely know where you belong. And if I read this again in fifty years, I may forget some names, but not the memories.

Finally, this is coming to an end. First, I would like to thank myself for being patient and perseverant enough to drag this across the finish line. To my parents, mom and dad, thank you for the constant reminder that you were fully prepared to fly over and make sure I finished this PhD one way or another. Your unwavering support, both financial and otherwise, made it possible for me to pursue this path while somehow maintaining a lifestyle that suggests I made better financial decisions than I actually did. You made it possible for me to pursue a PhD full-time, even though at this stage of life, a stable corporate career would have been the more expected path in our culture. And to my brother, thank you for providing just enough early-life motivation to keep me moving forward.

To my "SSE academic family": Sara Rosengren, for being the kind of mentor who gently but persistently pushes things to completion. I still remember sitting with you going line by line, brand by brand, category by category through grocery retail data until things finally started to make sense. Rickard Sandberg, for being supportive, understanding, and for always saying yes, especially to my reimbursement requests. With you, it was R code line by line, from linear models to non-linear ones, until they finally converged. Together, you taught me how things work, and occasionally, what we could have done differently. And Emelie Fröberg, the first person I met before this journey even started, and someone who has been there ever since. From academia to credit risk and everything in between, thank you for being there throughout. I suspect this is not the end of that journey.

Hannes Datta, my academic "adopted" parent from Tilburg University, thank you for taking me in and teaching me to be (arguably) great in both academia and industry. I know you would probably tell me not to be sentimental, but I will make a small exception here. My time in academia had its lowest points, including moments where statistically significant effect sizes I found approached e^{-6}, and even after rounding still showed up as

0.0000*, but also some of its best, many of which came from working with you. Thank you for believing in me when I did not, for giving me the opportunity to be part of your team, and for treating supervision more like coaching. We may not have a published paper together, but I hope I am, in some way, a reflection of your mentorship. You taught me how to think academically while being ready for industry, which I found more valuable than any 4-star job market paper. I am quite certain the lifetime returns from this mentorship will exceed e^6 EUR.

I would like to thank a few academics I had the chance to learn from along the way, especially Rik Pieters, Els Gijsbrechts, Marnik Dekimpe, Koen Pauwels, and Max Pachali, for offering some of the most expensive things a PhD student could ask for: free reviews of my papers, access to some of the best quantitative courses, and honest advice on navigating PhD life. I am also especially grateful to Anne Ter Braak and Lily (Xuehui) Gao for being my mock opponents and for providing one of the best mock defenses I could have experienced. I also appreciate the opportunity to be part of the IJRM newsletter, working together with Renana Peres and Martin Schreier, which gave me the chance to have one-on-one conversations with many inspiring academics, more than I can reasonably list here, but all featured in the newsletter for those curious.

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I cannot talk about this journey without mentioning my time as a research visitor in "Tilly." I really appreciated how generous the marketing department there was, from dinners to free drinks and bitterballen whenever we had guest speakers, and the PhD camps that made the experience even more memorable. Evenings at places like The Cat's Back were some of my favorite times with friends there. I also enjoyed long walks in the forest behind campus, often with a cigarette and a colleague, mostly talking about how to deal with endogeneity. Thank you as well to those who helped carry me back (literally) when I overestimated my limits. Some stories are probably best left undocumented.

To my colleagues at Nordea, the first place I joined after my PhD and my first role in industry abroad, thank you for giving me the opportunity to experience the best of both worlds. It was a place where I could contribute conceptually and be heard, without always needing to frame everything as a research gap or a theoretical contribution. I am especially grateful to Rene Eriksen for taking me in and for valuing my skills and knowledge, and for the support and understanding while I was still completing my PhD. And to all my colleagues at Nordea, thank you for making my first step into industry such a positive experience. I have not regretted leaving academia. This experience showed me that my PhD is, in fact, useful beyond its own field.

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Stockholm, April, 2026

Tanetpong (Ned) Choungprayoon

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Chapter 1

Introduction

1.1. Background

New multichannel and digital offerings are, along with increased data availability, major developments that have characterized the retail sector in the past decades (Bradlow et al., 2017; Cui et al., 2021; Dekimpe, 2020; Verhoef, Venkatesan, et al., 2010). Such advancements have given consumers access to a wide range of store formats and channels. In this thesis, *store format* is a term referring to any type of physical store (e.g., hypermarket, supermarket, or convenience store) whereas *channel* refers to the mode of access (e.g., online and offline).

Retailers can operate through traditional physical store formats, through online-only channels, or in multichannel retailing settings (i.e., environments where online and offline channels operate in parallel but are not necessarily fully integrated, as in omnichannel retailing; Verhoef, Kannan, et al., 2015). For example, the grocery store is a traditional store format where consumers shop in person using carts in physical aisles. As an online-only format, Amazon's early model was exclusively concerned with selling books online. A fashion brand such as H&M could be taken as a multichannel retailer because its customers browse and buy items either through a website or in a physical store. As customers increasingly use multiple formats and channels, retailers gain more data to better understand customer decisions and improve performance evaluation across formats and channels alike.

With alternative store formats and channels, retailers can offer various forms of access for and engage a broader consumer base as they seek to enhance the shopping experience (Verhoef, Kannan, et al., 2015). As products become accessible through more physical locations and digital touchpoints, retailers also have the option of expanding store formats and adopting additional channels to increase the visibility of their offerings (Lemon and Verhoef, 2016). Therefore, retail formats and channels do not only provide access to products; they also determine how prominently those products are exposed to consumers during the shopping process. In particular, distinct retail formats and channels can facilitate different shopping goals, whether in the same consumers or among consumers whose characteristics and shopping behaviors differ from each other. It is thus beneficial for retailers to understand differences in how consumers behave across formats and channels, and to grasp these consumers differences in terms of their demographic factors and purchasing behaviors (Verhoef, Venkatesan, et al., 2010). Such insights lead to important implications for retailers who aim to effectively design and customize their marketing mixes with respect to their consumers' needs (Breugelmans et al., 2023).

Retailers operating across store formats and channels have access to abundant data. This includes both macro-level data (e.g., total grocery purchases from particular demographic groups, or total number of global users on specific platforms) and micro-level data (e.g., individual or household purchases of certain categories, a single user's consumption history). Such data-driven 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 and delivered to). They may then use this data to understand their customer thoroughly, and to efficiently optimize their operations (Bradlow et al., 2017; van Heerde and Dekimpe, 2024). Digital platforms such as Spotify or eBay also operate as retailers by offering products and services directly to customers, often without physical constraints. Platforms can leverage detailed customer data to produce better products and enhance customer loyalty (Smith and Telang, 2016). Similar to physical retailers' decisions on shelf placement and in-store displays, digital platforms place products and content for users to experience through curated lists, rankings, and recommendations. In addition to data collected directly by retailers, publicly available information can be extracted from the internet via web scraping or APIs to generate further insights. These web-based data sources offer valuable context for understanding the market, consumer behavior, and competitive positioning across retailers (Bonfrer et al., 2022; Guyt et al., 2024).

These developments offer opportunities and challenges for retailers and researchers alike. On one hand, diversity in retail formats allows businesses to tailor offerings for different customer segments and shopping contexts. For example, as Forbes (2024) highlights, leading retailers are shifting from a one-size-fits-all model. As they customize store formats, product assortments, and services to meet the specific needs of segments such as Gen Z, millennials, and diverse cultural communities, retailers are becoming known as "support partners" for distinct groups of shoppers. On the other hand, in its volume and complexity, the available data demands 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 structured data strategies aligned with business processes and decision-making. This approach ensures that data interpretation aligns with clear business objectives while reducing the influence of individual bias.

A deeper integration of insights is now required of consumer behavior research, empirical methods, and analytics as they focus on understanding consumer behavior, designing effective pricing strategies, and evaluating performance across channels. Insights act as a lens to interpret the observable patterns revealed by data, and data sharpens that focus by validating assumptions and uncovering causal relationships. Data thus becomes not just a tool for operational improvement but a means of systematic quantification regarding how customers respond to strategic decisions (and how those responses translate into retail performance).

1.2. Problem Formulation

Despite major advancements in data collection and marked expansion of retail formats and channels, using these developments to generate actionable insights about performance remains far from straightforward. Retailers still face several challenges in evaluating the outcomes of their strategic decisions. The challenges are especially pronounced when consumer behavior is used as the primary lens for evaluation. Because consumer behavior cannot always be directly observed, it must often be inferred from observable responses captured in data which often involves complex, context-specific responses that are difficult to isolate and interpret. Because consumer responses can vary widely across retail environments, retailers must go beyond tracking what happened to understanding why it happened, and eventually to grasping how it matters for future decisions (McKinsey & Company, 2025). Doing so requires an approach that integrates empirical analysis with established insights from consumer behavior literature to yield observations that are both theoretically sound and practically relevant. Four issues lend to the overall research problem which this thesis aims to address.

First, the growing reliance on data-driven approaches has not always been matched by the integration of theory and explanation. Retailers and researchers have access to vast volumes of behavioral data. However, while it may trace any number of behaviors—ranging from those exhibited during individual shopping experiences at physical stores to aggregate behavior on online platforms—more data does not inherently mean more insights. Without theoretical grounding, analysis can become reactive or descriptive at best. In other words, such 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. Yet, to be actionable, guidance should be grounded in causal understanding, and it should be 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 goals and customer expectations. For example, a customer may visit a hypermarket for planned, bulk shopping (e.g., detergent, milk) and a convenience store for quick, impulsive purchases (e.g., snacks). Despite the differences, retailers often apply uniform pricing and promotions across formats without fully accounting for how the same customer may respond differently depending on the setting. These challenges become even more pronounced when retailers target various customer segments by managing multi-tier private label (PL) portfolios that offer economy, standard, and premium products within the same category. Because the products are controlled by the retailer, pricing decisions across PLs tiers directly influence both customer choice and retailer margins. This creates uncertainty about the effectiveness of pricing strategies and raises a broader challenge. How should retailers design and evaluate pricing decisions when customer responses vary by format?

Third, when physical retailers introduce an online channel, it creates strategic uncertainty about long-term customer behaviors and business outcomes. While digital channels often increase convenience and expand access, they also influence how customers interact with the retailer over time. Some customers may shift their purchase volume online, while others may change product mix, basket size, and purchasing frequency (e.g. Ansari et al., 2008; Li, Konuş, et al., 2015; Melis et al., 2016). 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 (in terms, e.g., of visit frequency, basket size, or category choice), and it impacts retailer revenue and profitability.

Fourth, consumer behavior on digital platforms is increasingly influenced by curation systems that determine which products, assortments, or contents receive exposure. In this context, exposure can be understood as a form of product visibility that shapes what consumers encounter in large digital assortments. For online-only environments like music streaming platforms, algorithmic and editorial curation shapes what users see and how they respond to products or content. Systems either amplify already-popular items or give visibility to emerging or independent content providers (e.g., Brynjolfsson et al., 2010). Platforms and retailers can thus act as gatekeepers of attention by influencing which products are noticed and ultimately consumed. Because consumer responses interact with such exposure, changes in the broader environment can also affect how consumers respond. External shocks such as the COVID-19 pandemic can shift user behavior and content consumption patterns. Accordingly, such shocks indirectly affect who gains or loses visibility. The broader challenge is to understand how, particularly in contexts where attention is scarce and competition is high, platform design and curator roles influence performance outcomes.

Together, these challenges point to a broader need to understand (by accounting for how consumers perceive, interpret, and respond) strategic retail decisions' effects on business performance. Retailers influence consumer responses through multiple strategic instruments including pricing decisions, expansion of access through store formats and channels, and management of product visibility across physical and digital environments. This thesis thus responds to this broader need by drawing on established consumer behavior literature and applying empirical models to large-scale data to examine how pricing strategies, channel additions, and digital exposure influence performance outcomes such as sales and profitability.

1.3. Research Purpose and Questions

The purpose of this thesis is to examine how strategic retail decisions, including pricing, channel introduction, and product exposure on digital platforms, influence customer behavior and thereby affect performance outcomes. By empirically modeling observable customer responses across store formats, channels, and digital platforms, the aim is to demonstrate how data-driven approaches, informed by consumer behavior research, can generate actionable insights for retailers.

This leads to the overarching research question: **How do retail strategies related to price, channel access, and product visibility shape customer behavior and ultimately influence retail performance across different formats, channels, and digital platforms?**

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

1. How do pricing strategies among PLs 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 within the same retail chain?

3. What are the long-term effects of online channel adoption on customer behavior and retailer revenue?

4. How did changes in product visibility and content on digital platforms affect customer behavior during the COVID-19 pandemic?

1.4. Outline of the Thesis

The remainder of this thesis is organized as follows. Chapter 2, drawing on key concepts from consumer behavior research, introduces the theoretical framework to guide the empirical investigations. Chapter 3, highlighting how different modeling approaches are applied in multiformat, multichannel, and digital platform contexts, outlines the data sources and empirical methods used across the four studies. Chapter 4 presents the four studies and discusses their individual contributions in terms of the research sub-questions. Chapter 5 jointly discusses the four studies' theoretical contributions, managerial implications, methodological considerations, and limitations; it then notes their implications for future research. Finally, the Epilogue offers a personal reflection on the research process and a few confessions from crossing back and forth between academia and industry.

Chapter 2

Theoretical Background and Framework

The theoretical background focuses on three domains. The first concerns pricing strategy across retail formats, where retailers decide how to position and differentiate products through regular prices, discounts, and multi-tier offerings to influence purchase decisions and profitability. The second involves online channel introduction, where retailers launch additional channels and determine how online and offline channels jointly shape customer convenience, shopping patterns, and long-term value. The third addresses visibility strategies on digital platforms, where platform operators and participants manage exposure to influence how customers respond to products or content. Together, these domains capture how retailers and platforms can use marketing instruments to influence customer responses, which in turn shape performance. Rather than treating customer behavior as a black box, this chapter frames it as the lens through which the effects of retailer actions on customer responses and performance outcomes can be interpreted and explained. While academic research often seeks to explain why customers respond in certain ways, practical applications and some empirical work still focus primarily on measurable outcomes (i.e., on what happened) rather than on mechanisms that drive such outcomes. This thesis emphasizes the importance of reconnecting outcomes with the underlying mechanisms, of recognizing that performance depends not only on what retailers do but also on how customers perceive and respond to those actions. The remainder of this chapter is structured as follows. Sections 2.1 to 2.3 review theoretical insights across the three domains. Section 2.4, highlighting how each study connects strategic decisions, customer mechanisms, and performance outcomes, synthesizes these perspectives into an integrated framework that links theoretical concepts to the empirical studies.

2.1. Customer Response to Pricing Across Store Formats

Retailers operating across multiple store formats must decide how to set and manage prices in alignment with customer expectations, the promotion of sales, and the preservation of profitability. This can be challenging, especially when shoppers may expect consistent pricing across locations operated by the same retailer (e.g., Gauri et al., 2021). Store formats like the hypermarket, supermarket, and convenience store serve distinct shopping goals which influence how customers respond to pricing decisions (e.g., Bonfrer et al., 2022). While retailers often differentiate prices according to format to reflect these shopping missions, customer perceptions may not always align with these strategic distinctions, particularly when stores share branding or operate in close physical proximity to each other.

Traditionally, physical retail formats have been defined by differences in size, assortment depth, price level, location, and customer service levels (Bonfrer et al., 2022). Hypermarkets, for instance, tend to attract bulk shoppers and value seekers, while convenience stores suit quick trips and impulse needs. These format-driven missions affect how customers perceive prices and respond to promotions. Haans and Gijsbrechts (2011) find that, even within a single retailer, the same promotion can have different effects depending on the format. This variation is linked not only to differences in store missions but also to how customers form and apply reference prices, defined as internal benchmarks drawn from memory or expectations that influence how attractive a given price appears (Mazumdar et al., 2005; van Oest, 2013).

In practice, retailers rely on two primary pricing mechanisms: lowering regular price levels (i.e., adjusting retail prices) and offering temporary promotional discounts (i.e., temporary reductions in price). These two pricing mechanisms influence customer behavior in different ways. Regular price cuts may reinforce value perceptions over time but erode margins if not carefully planned (e.g., Lalwani and Monroe, 2005; Zeithaml, 1988). Promotions, on the other hand, can stimulate short-term demand but may also encourage deal-seeking behavior and purchase postponement (e.g., Hamilton and Chernev, 2013). The effectiveness of these tools depends on the store format and customer base. For instance, customers at hypermarkets may be more deal-driven and responsive to deep discounts, whereas those at convenience stores might be more time-sensitive and less price-elastic (Ailawadi, Pauwels, et al., 2008; Weathers et al., 2015).

Beyond these pricing instruments, retailers increasingly manage pricing strategically through their brand portfolios, particularly through the use of multi-tier PLs. In contemporary retail environments, consumers frequently encounter assortments that include both national brands and multiple tiers of PLs, such as economy, standard, and premium offerings, within the same product category. This phenomenon reflects broader changes in the retail landscape, where store brands no longer serve solely as low-price alternatives but instead span a range of quality and price positions comparable to national brands (Keller and Sethuraman, 2026). Because a PL is fully controlled by the retailer, it provides greater flexibility in setting prices, managing margins, and shaping substitution patterns within the assortment. Retailers can strategically position different tiers to attract value-seeking customers, encourage trading up within their own portfolio, and manage competition with national brands. As a result, pricing decisions involving PL tiers may influence retailer performance more directly than pricing decisions involving manufacturer brands.

The effectiveness of pricing strategies also varies across categories and brands (e.g., Osuna et al., 2016). 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 (e.g., Dhar et al., 2001; Raju, 1992). More broadly, recent empirical research shows that the effectiveness of marketing mix instruments (including price, assortment, and distribution) varies substantially across brands, categories, and market contexts, thus reflecting underlying differences in market conditions and consumer responses (Gielens and Steenkamp, 2025). As a result, retailers must tailor their overall pricing approach to reflect both format-specific customer 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. The literature has established that pricing outcomes vary across store formats. However, less is known about multi-tier PLs' overall performance in different retail environments under the same retailer, or about how pricing strategies (including reducing regular prices versus offering promotions) influence customer behavior at the format level. The first study addresses this gap by examining the format-specific responsiveness and profitability of PL tiers. The second study investigates how the effectiveness of regular price changes and temporary promotions varies across categories, brand types, and store formats.

2.2. Customer Decision-Making and Channel Adoption

The rise of online shopping has reshaped the retail landscape by giving rise to models where physical and digital channels coexist in what is commonly termed multichannel retailing (Verhoef, Kannan, et al., 2015). Unlike exclusively online or physical formats, this multichannel structure introduces 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., Li, Konuş, et al., 2015; Wang 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 customer behavior, and to assess whether online adoption leads to sustained value creation or merely shifts spending to a costlier channel (e.g., Neslin and Shankar, 2009; Reinartz et al., 2019; Verhoef, Venkatesan, et al., 2010).

From a consumer perspective, channel choice can be modeled as a utility-maximizing decision where consumers weigh trade-offs between convenience, assortment, price transparency, and immediacy (Ansari et al., 2008). The same consumer may pursue different shopping goals across channels, for example using online platforms for stock-up trips or product research while relying on physical stores for immediacy and tactile evaluation (Campo, Lamey, et al., 2020). These channel preferences are further shaped by situational factors such as trip purpose, time constraints, and promotional activity (e.g., Neslin, Grewal, et al., 2006; van Nierop et al., 2011).

Building on this perspective, the theory of shopping utility maximization (Campo, Lamey, et al., 2020) distinguishes between acquisition utility and transaction utility. The former is defined as benefits derived from the product itself, such as price or assortment. The latter is defined as benefits related to how easily and conveniently the product can be obtained. In grocery retail, prices and assortments are often similar across channels. As a result, the decision to purchase online or offline is typically 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, Neslin, 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 of goods online, others (especially in low-involvement categories like groceries) exhibit reduced variety, fewer impulse purchases, and more repetitive purchasing patterns (Chintala et al., 2023). Such behavioral adjustments may also develop over time rather than immediately after channel adoption. Customers may initially experiment with the online channel before incorporating it into their regular shopping routines. As they gain experience and interact repeatedly with the retailer, their purchasing patterns may adjust accordingly. Consumer behavior research suggests that preferences and usage patterns evolve through accumulated experience and customer–firm interactions over time (Zhang and Chang, 2021).

Prior research has examined immediate changes in shopping behavior following online channel adoption, but the long-term effects remain less understood. Most studies focus on short-term changes in activity and, to date, few explore how behavior evolves over time, particularly among existing customers (e.g., Campo, Lamey, et al., 2020; Wang et al., 2015). A question for both retailers and scholars, therefore, is whether digital channel adoption generates incremental, sustainable customer value or just shifts customer 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. It investigates how purchasing shifts across product categories following adoption, and whether these behavioral changes persist over time and ultimately translate into sustainable value creation for retailers.

2.3. Customer Behavior on Digital Platforms

As retail shifts into digital spaces, the mechanisms that govern customer behavior increasingly diverge from traditional models. In traditional physical environments, exposure is shaped by store environments such as shelf placement, store layout, and signage (e.g., Baker et al., 2002; Donovan et al., 1994). On digital platforms, however, visibility is governed by algorithmic and editorial curation (e.g., Aguiar, Waldfogel, and Waldfogel, 2021). Platforms such as Spotify, Amazon, and eBay act not only as marketplaces but also as gatekeepers of influence; they decide which products, contents, or sellers are surfaced (e.g., Jürgensmeier and Skiera, 2025; Rietveld, Schilling, and Bellavitis, 2019). These systems, by making exposure itself a central competitive resource, structure what customers see, click, and respond to (e.g., Rietveld and Schilling, 2021; Zhang, Li, et al., 2022).

In digital environments, this gatekeeping role is implemented through mechanisms such as search rankings, recommendation systems, and curated collections that determine which options appear most prominently to users. Recommendation systems, in particular, suggest products or content based on past behaviors, preferences, and similarities with other users, helping customers discover items they might otherwise overlook (Gai and Klesse, 2019). At the same time, retailers and platforms can influence these recommendation environments through curated selections, promoted placements, and algorithmic design choices that determine which products receive greater visibility. These systems recommend products, summarize reviews, and rank alternatives, often by presenting a shortlist of options before consumers visit a retailer's website (Bain & Company, 2025). As a result, visibility within these systems becomes a key determinant of customer responses and competitive outcomes in digital marketplaces.

In music streaming, for example, customer behavior is directed through curated playlists and recommendation algorithms that govern content discovery. Prior research has highlighted the dual role of platforms, 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 (Aguiar, Waldfogel, and Waldfogel, 2021; Anderson, 2006; Bar-Isaac et al., 2012). 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 behavioral patterns to shape visibility, curators introduce human judgment, editorial intent, and identity signaling into what users discover (Pachali and Datta, 2025).

External shocks can affect these dynamics. The COVID-19 pandemic, for instance, shifted consumption patterns and changed the baseline for user responses (e.g., Sim et al., 2022). However, it remains unclear how these shifts affected participants on the platform, particularly those involved in content curation. In the context of music streaming, playlist followers represent a key form of user behavior (i.e., observable interaction) that reflects user attention and potential consumption on the platform. Playlist exposure can substantially increase streaming demand, illustrating that visibility within curated playlists can directly influence consumption outcomes on digital platforms (Wlömert et al., 2025). However, follower growth is not evenly distributed across curator types. Platform-owned playlists often enjoy prominent placement and their own algorithmic support; label-owned and independent curators, by contrast, face more variable exposure (Aguiar, Waldfogel, and Waldfogel, 2021; Pachali and Datta, 2025). These structural asymmetries can amplify existing inequalities, especially during a pandemic.

The fourth empirical study in this thesis, by analyzing changes of follower across curator types on Spotify before and after the COVID-19 pandemic declaration, addresses the issue of customer behavior on digital platforms. It thus contributes to a broader understanding of how customer behavior, reflecting the interplay between user behavior and platform structure, evolves under external disruptions. These mechanisms illustrate that customer responses on digital platforms are not merely reflections of customer preferences but products of mediated exposure where algorithms, editorial choices, and platform architecture shape what users encounter and how they respond. From a broader retail perspective, these processes parallel how assortment visibility, shelf placement, and promotional emphasis influence customer choices in digital settings. Understanding these parallels extends existing retail theory by emphasizing visibility and exposure as central elements of strategic decision-making, particularly in environments where customer attention has become a scarce and managed resource.

2.4. An Integrated Framework Linking Theory and Empirical Studies

The three preceding sections reviewed distinct yet interconnected streams of research on customer behavior in response to retailers' strategies. While each domain addresses different strategic decisions, they all share an emphasis on how customers respond to retailers' actions across different contexts. These responses, observed through purchasing behavior, channel use, and interactions on digital platforms, eventually shape retailer performance.

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

This structure applies across all four studies in the thesis. Each study investigates how a particular strategic action alters the customer decision-making context, and how that in turn affects performance outcomes such as sales, profitability, customer retention, and platform-based responses. While the empirical analyses focus on observable customer responses, the theoretical domains reviewed in this chapter provide guidance for interpreting the mechanisms that may underlie these responses. Because the analyses rely primarily on aggregated behavioral data, the intermediate decision processes of individual consumers cannot be directly observed but are instead inferred through theory and prior research (Hanssens and Pauwels, 2016). Table 2.1 summarizes the conceptual focus of each study.

Study	Strategic retail decision	Theoretical domains	Observable customer response: Key mechanism	Performance outcome
1	Setting price for multi-tier PLs across formats	Pricing across store formats; private label strategy	Purchase decision: Customers compare relative prices across PL tiers and perceive value differently	Sales, profits
2	Adjusting regular price or offering promotions across formats	Pricing across store formats; reference price effects and price framing	Purchase decision: Customers perceive changes in regular price and discounts differently	Sales
3	Channel introduction	Multichannel retailing; shopping utility and digital complementarity	Purchase decision: Customers, through changes that may not persist over time, adjust purchasing behavior after adopting the online channel	Category purchases, revenues
4	Management of product exposure on digital platforms	Platform economy: Consumer behavior on digital platforms	Following decision: Customers have limited attention and need to choose certain contents to fit with their current situations	Platform-based responses (e.g., playlist followers)

Table 2.1. Summary of Theoretical Domains and Empirical Focus Across Studies

This framework connects strategic retail actions, customer responses, and performance outcomes. Since these responses are context-dependent, empirical investigation helps quantify how the effects of strategies vary across contexts. Across the domains examined, the studies demonstrate how theoretical insights concerning (e.g.) reference price effects, shopping utility maximization, and platform economy provide a basis for interpreting observable customer responses. These insights provide explanations for why customer responses differ across contexts and how they translate into specific performance outcomes. Moreover, because theory can yield conflicting expectations across contexts, empirical analysis is important for assessing which explanations are more consistent with the data. Taken together, theory and empirics are closely linked: theory guides what to measure and examine while empirical evidence validates and refines theoretical relationships.

Chapter 3

Data and Methodology

This chapter outlines the empirical strategies used across the four studies in this thesis. It demonstrates how established empirical techniques are applied to different retail settings to examine the effects of strategic decisions on customer behavior and performance outcomes. Studies 1–3 rely on transaction-level data from a grocery retailer loyalty program; Study 4 uses publicly available data from the Spotify music streaming platform. Across these contexts, quantitative modeling approaches are designed to quantify how strategic retail decisions influence customer behavior and resulting performance outcomes. Table 3.1 provides a summary of the four empirical studies, including context, data source, its coverage, method, and level of analysis for performance outcomes. Each section then describes the research setting, data and sample construction, modeling approach, and limitations related to both data and modeling choices.

Study	Context	Data source	Coverage	Method	Level of analysis
1	Multiformat retailing	Retailer scanner data from loyalty program	135,776 shopping trips over five selected product categories based on 4,921 customers	Error-correction model of sales response with price elasticity estimation and subsequent profit elasticity	Weekly brand sales
2	Multiformat retailing	Retailer scanner data from loyalty program	897,743 shopping trips from 5,468 customers	Two-stage approach: Price elasticity estimation and analysis of the moderator	Weekly brand sales
3	Multichannel retailing	Retailer scanner data from loyalty program	116,982 shopping trips across 578 households (147 of which adopt an online channel)	Propensity score matching combined with difference-in-differences estimation	Weekly customer purchases
4	Digital platforms	Spotify playlist API and web-scraped data	39,918 playlists with 49 consecutive weeks of follower data	Playlist-level unit fixed effects panel regression	Weekly playlist followers

Table 3.1. Overview of empirical contexts, data, and methods across studies

3.1. Multiformat Retailing (Studies 1 and 2)

The first two empirical studies are situated within the context of multiformat grocery retailing. They examine how pricing strategies perform, across different store formats, for one multi-format retailer. Despite belonging to the same retail chain, different formats cater to distinct shopping goals and create a unique context to explore customer responses to pricing decisions across different physical stores.

The data comes from the loyalty program of a major grocery retailer that operates in three store formats: hypermarkets, supermarkets, and convenience stores. From large-format stores catering to stock-up trips to medium-sized stores serving regular household needs and small outlets focused on immediacy and proximity, these formats differ substantially in size, assortment, and price positioning. Because shopping missions, basket sizes, time constraints, and assortment breadth systematically vary across these formats, customers are likely to respond differently to regular prices and promotions. For example, price discounts may be more salient for large, planned baskets at hypermarkets than for quick, convenience-driven trips at small stores. Promotional campaigns are coordinated centrally, while individual store managers retain flexibility in setting regular prices based on local market conditions. Taken as a whole, the situation reflects a multi-format strategy that combines service-oriented and price-competitive elements. Rather than following a strict everyday-low-price policy, the retailer maintains competitive regular prices but also relies on centrally coordinated promotions. This strategy is consistent with a hybrid or moderated hi–lo pricing format that lies between pure everyday-low-price and pure hi–lo in grocery retailing. The dataset includes 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 customer behavior and pricing outcomes. From this dataset, study-specific samples are selected based on the requirements of each empirical design, resulting in differences in sample size and composition between Studies 1 and 2 (see Table 3.1).

To evaluate how pricing strategies affect sales and profitability across physical store formats, the first two studies model customer responses using aggregated brand-level sales data. Aggregate sales response models are commonly used in retail pricing research because pricing decisions are typically implemented at the brand or category level rather than at the individual-customer level. Using brand-week panels therefore aligns the empirical model with the level at which retailers observe performance and make pricing decisions. Compared with individual-level choice models, this approach also reduces computational complexity while still capturing meaningful variation in customer responses to prices and promotions across store formats (Datta, van Heerde, et al., 2022; Pauwels et al., 2007). Thus, the unit of analysis of these studies is at the brand-week level, aggregated from transaction data, allowing the studies to quantify market-level customer 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.

To align with this modeling approach, the two studies leverage the same dataset to construct comparable brand-level sales panels across the three formats. The analysis focuses on the three store formats belonging to the same retail chain, located in the same area, for the purpose of ensuring the consistency and comparability of formats. To avoid biases due to assortment variation, products were selected based on consistent availability (a) across all three formats and (b) throughout the observation period, with an emphasis on frequently purchased brands. To ensure that any observed pricing effects were not confounded by size-based price differences, only items with standardized package sizes were retained. This approach mitigates the risk that format-based variation in sales is driven by differences in what is stocked, rather than by how customers respond to pricing.

In the first study, the focus is on profit-oriented evaluation of regular price setting for multi-tier PLs. The modeling follows a multi-step regression framework. First, price elasticities are estimated for each PL tier and format using observed variation in prices paid 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 (e.g., Geyskens et al., 2010; Keller, Geyskens, et al., 2020; ter Braak et al., 2013).

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, and 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 with respect to brand and category factors (e.g., Datta, van Heerde, et al., 2022; Haans and Gijsbrechts, 2011; Pauwels et al., 2007).

Both studies apply a sales response modeling framework (e.g., Pauwels et al., 2007), capturing how changes in price influence weekly sales volumes. An error correction specification is used because it allows the model to separate immediate demand reactions from longer-run equilibrium adjustments, which is particularly important when prices and promotions vary frequently across weeks. 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, and promotional cycles (Datta, van Heerde, 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 category level (Widdecke et al., 2022). 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 elasticity and translating those effects into strategic insights about pricing, promotions, and profitability across brands, categories and formats.

While the dataset focuses on loyalty card holders from a single retail chain, it offers a high degree of consistency and detail, allowing precise observation of behavioral and sales dynamics over time within a stable customer base. Several limitations should however be acknowledged. First, the data do not capture purchases made at competing retailers; this may limit the generalizability of findings beyond the focal chain. Second, the analysis focuses on products consistently available across formats and time, enhancing comparability but possibly excluding niche or newly introduced items that could behave differently. Third, as the data reflect pricing and assortment decisions within one retailer's organizational structure, some format-specific effects may be influenced by chain-level strategies that are not directly observable. In addition, the aggregate structure cannot capture within-brand heterogeneity in customer responses—for example, how different shopper segments may react to a given promotion (Ailawadi and Harlam, 2004; Geyskens et al., 2010). Furthermore, observed price variation is not randomly assigned and may reflect broader retailer strategy, so caution is required in interpreting causal claims (Bijmolt et al., 2005; Datta, van Heerde, et al., 2022). Despite these limitations, the combination of careful sample construction, consistent product selection, and inclusion of fixed effects for products, time, and store formats helps mitigate potential confounds from unobserved heterogeneity. This provides a reliable basis for assessing how pricing strategies influence performance across store formats.

3.2. Multichannel Retailing (Study 3)

The third empirical study, focusing on how customer purchase behavior evolves following the introduction of an online shopping channel, is set in the context of multichannel grocery retailing. Like the previous studies, it relies on transaction data from the retailer's loyalty program, but it shifts the focus from store-format pricing to customer-level behavioral changes following online channel adoption. This setting provides a quasi-experimental setting 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. [1]

The data come from the loyalty program of the same grocery retailer assessed in Studies 1 and 2, covering a four-year period that spans both pre- and post-introduction periods 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 combines two consecutive panels (October 2014–November 2016 and August 2017–July 2019) and tracks 578 households (147 of which adopt the online channel) across 116,982 shopping trips and roughly 1.75 million purchased products. The dataset includes customer-level purchase histories across 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 identify the causal effect of online channel adoption on purchasing behavior, the study employs customer-level panel modeling techniques based on propensity score matching (PSM) and difference-in-differences (DiD) estimation. This approach is appropriate because online channel adoption is a voluntary decision rather than a randomized treatment. Propensity score matching, to reduce observable selection bias, first constructs comparable groups of adopters and non-adopters based on pre-adoption shopping behavior. Difference-in-differences estimation then exploits the panel structure of the data to

[1]According to Goldfarb et al. (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.

compare behavioral changes before and after adoption at the customer level, thus helping isolate the causal impact of channel adoption from common time trends (Boehm, 2008; Campo and Breugelmans, 2015).

To align with this modeling approach, the study leverages the loyalty data's panel structure to track individual customers 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 a panel of customers across a multi-year window (covering the before and after of the online channel's introduction), the study captures longitudinal changes in behavior that follow the introduction and adoption of this new shopping format (Avery et al., 2012; Bilgicer et al., 2015). This quasi-experimental setting allows the model to distinguish between behavioral changes caused by adoption versus those driven by general time trends or unobserved customer characteristics (Li, Konuş, et al., 2015).

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 and 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, Konuş, et al., 2015), while DiD specifically controls for time-invariant unobservables and shared temporal trends.

While the dataset offers a unique opportunity to study an effect of online channel adoption on customer purchase behaviors, 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; these are not explicitly accounted for. Second, because purchasing activity varies across customers, the ability to model detailed temporal dynamics (e.g., behavioral changes after one, two, or three years of adoption) is limited. Third, 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. In addition, 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 and Van den Bulte, 2023). This assumption cannot be directly tested and may become less plausible as the post-adoption period extends. While matching helps improve group comparability, the use of proxies such as diaper purchases and store distance may not fully capture deeper household characteristics. Furthermore, DiD is less effective when treatment timing varies across individuals, or when adoption reflects structural changes in customer behavior that evolve gradually rather than in discrete shifts (Roth et al., 2023). Despite these limitations, matching and DiD allow comparison of purchasing behavior between adopters and non-adopters over time. The combined use provides a transparent and meaningfully practical basis for assessing how online channel adoption affects customer behavior over time.

3.3. Digital Platforms (Study 4)

The fourth empirical study is situated in the context of digital platforms, where customer behavior can be largely shaped by platform structures and mechanisms such as algorithmic curation and editorial decisions. Because these systems determine what users see and engage with, they influence which participants on the platform gain attention, or traffic. In such environments, potential external disruptions like the COVID-19 pandemic can alter user behavior at scale, raising questions about how users interact with content shift after the onset of such an event. Unlike the other studies, which rely on retailer loyalty data, this one uses publicly available platform data to examine observable user responses in a digital marketplace.

The data are extracted from publicly available sources related to Spotify, one of the world's leading music streaming platforms. The dataset combines two primary sources. First, playlist-level follower data was 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 Every Noise at Once is 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 user responses) and platform-driven exposure. 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 final sample consists of 39,918 active playlists with 49 consecutive weeks of data spanning October 2019 to October 2020, thus covering periods before and after the pandemic was declared.

To examine changes in user responses on the platform, the study models playlist follower growth using fixed effects panel regression. Weekly follower changes serve as a proxy for aggregate observable user responses. A fixed effects panel specification is used because playlists differ systematically in their baseline popularity, genre, and curator characteristics. By controlling for these time-invariant playlist attributes, the model isolates within-playlist changes in follower growth over time (Papies et al., 2022).

To align with this modeling approach, the dataset is structured as a playlist-level panel observed over time, thus allowing each playlist to be tracked before and after the pandemic declaration. Each playlist serves as an observation unit, with time-varying attributes such as follower counts, content composition, curator type, and promotional exposure. The resulting dataset enables comparison of changes in follower growth within the same playlist over time, rather than across inherently different playlists. Key independent variables include playlist curator type, content composition, and weekly indicators of platform-driven promotion (i.e., Search Page featuring).

This modeling 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, allowing changes in follower growth to be more closely associated with the pandemic period rather than general time trends.

First among limitations to be noted with regard to the fourth study, the dataset captures publicly observable playlist-level metrics such as follower counts rather than individual user behavior, and this leads to limited insights concerning the micro-level drivers of engagement. Second, the influence of Spotify's algorithmic or editorial decisions is not directly observable and must be inferred from the featuring data. Third, follower growth serves as a proxy for user response and does not capture listening intensity or financial outcomes. In addition, the fixed effects model might be better suited for estimating large, persistent changes in engagement rather than subtle or short-lived shifts. As such, for smaller effects (particularly those limited to a subset of playlists or time periods) it may be harder to isolate the effect with certainty and subject to attenuation. Finally, even with week fixed effects, any unobserved time-varying shocks that affect playlists differently may not be fully captured by the model structure. Despite these constraints, the panel structure and fixed effects specification allow for consistent measurement of changes in user responses over time, particularly in response to large-scale external disruptions such as the pandemic (Denk et al., 2022; Sim et al., 2022).

Chapter 4

Empirical Studies

This chapter presents the four empirical studies. The following sections detail each study's motivation, empirical design, key findings, and contributions. While each study targets a specific decision and context, they collectively illustrate how data-driven approaches, grounded in consumer behavior theory, can be used to assess the effectiveness of strategies across formats, channels, and digital platforms.

4.1. Study 1

From Price to Profit: Multi-Tier Private Label Response Across Retail Formats
Authorship: Tanetpong Choungprayoon (Stockholm School of Economics)
Status: Working paper. An earlier draft was presented at the 53rd Annual Conference of the European Marketing Academy in 2024.
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Retailers increasingly use PLs not only to enhance margins but also to differentiate their assortments and target heterogeneous customer segments across store formats. Multi-tier PL strategies (typically comprising value, standard, and premium tiers) enable retailers to address heterogeneous customer preferences and strengthen store identity. However, the effectiveness of these tiers depends on store context. The same price change may have different consequences across formats that differ in assortment and in the shopping missions and customer expectations they facilitate. This study examines how price elasticities of multi-tier PLs (and the resulting profit effects of pricing decisions) vary across hypermarkets, supermarkets, and convenience stores.

Previous research has established the growing importance of PLs and the benefits of tiered strategies (Ailawadi, Pauwels, et al., 2008; Geyskens et al., 2010), but empirical evidence on how these effects differ across retail formats remains limited (Keller, Dekimpe, et al., 2022). While prior work shows that customer price responsiveness can vary across store formats (e.g.,Haans and Gijsbrechts, 2011), existing studies often treat PL pricing as uniform, overlooking the possibility that store format moderates both customer price sensitivity and cross-tier interactions. This study addresses the research gap by quantifying how pricing responses differ across tiers and formats, and by linking these responses to profit outcomes.

To analyze the effectiveness of PL pricing across tiers and formats, the study employs a two-stage modeling framework linking demand responses to profitability outcomes. The specification captures the interdependence among PL tiers by incorporating cross-price effects across tiers. First, 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 (e.g.) the value tier influence sales in (e.g.) the premium tier. Short-term elasticities are normalized to enable comparison across categories and formats, and are used to simulate expected changes in sales volumes under different pricing conditions. Second, 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, customer price responsiveness varies significantly across formats, even within the same PL tier and category. Second, cross-tier pricing effects are nontrivial, meaning that offering a discount on 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.

4.2. Study 2

Regular Prices vs. Discounts: How Pricing Strategies Perform Across Store Formats

Authorship: Tanetpong Choungprayoon (Stockholm School of Economics), Rickard Sandberg (Stockholm School of Economics), and Sara Rosengren (Stockholm School of Economics)

Status: Working paper. An earlier draft was presented at the 51st Annual Conference of the European Marketing Academy in 2022.

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Retailers frequently rely on two key pricing tactics to drive sales: adjustments to regular prices and the use of promotional discounts (i.e., temporary price cuts). While both tools can influence customer behavior, they are not equivalent in either perception or outcome. This study examines how regular price changes and promotional discounts differentially affect sales across retail formats within the same grocery chain. The analysis builds on the idea that shopping goals vary across formats, even for the same customers, yielding diverging responses to price cues.

Existing literature has highlighted the psychological distinctions between regular prices and promotional discounts (e.g., DelVecchio et al., 2006; Shankar and Krishnamurthi, 1996). While prior research has explored how customers respond to price changes, fewer studies have empirically disentangled the effects of regular price changes and promotional discounts across different store formats within the same retail chain. This study leverages an important feature of the empirical setting: promotional campaigns are largely centrally coordinated, while individual store managers retain flexibility in setting regular prices.

The analysis is based on data from a grocery retailer. It draws on three stores, one representing each format: a hypermarket, a supermarket, and a convenience store. All three are located in the same geographic area to minimize demographic and regional variation. Categories, products, and brands are selected based on consistency of purchase across format and time, allowing reliable cross-format comparison of price responsiveness. In the first stage of the analysis, we estimate regular price and discount elasticities for brand sales using an error-correction model of sales response following Pauwels et al. (2007), with controls for category traffic and trip types (major, fill-in, and unplanned). These controls help account for differences in shopping behavior across formats. In the second stage, we regress the estimated elasticities on brand- and category-level attributes such as discount frequency, discount depth, PL status, storability, and category competitiveness to examine how these characteristics explain variation in pricing effectiveness across formats.

The findings reveal three key insights. First, regular price elasticities are negative across all store formats, with the strongest magnitude in hypermarkets and the weakest in convenience stores. Discount elasticities are also highest in hypermarkets, followed by supermarkets, indicating stronger responsiveness to promotional pricing in larger formats. 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, depending on format and positioning, PLs show distinct patterns in their responses to price cues.

4.3. Study 3

The Long-Term Effects of Online Channel Adoption in Grocery Retailing

Authorship: Tanetpong Choungprayoon (Stockholm School of Economics), Emelie Fröberg (Stockholm School of Economics), and Sara Rosengren (Stockholm School of Economics)

Status: The current draft was initially given a "reject and resubmit" decision and was later rejected by the *Journal of Retailing*.
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The introduction of digital channels has reshaped grocery retailing by offering consumers greater flexibility while posing new challenges for retailers. Many studies have examined who adopts online grocery shopping and why, but fewer have explored how purchasing behavior evolves in the long term after adoption. This study investigates how customer purchase behavior changes after the introduction of an online channel, and whether such adoption leads to sustained revenue growth for the retailer.

Previous research shows that adding new channels can benefit retailers because multichannel customers often spend more than single-channel shoppers (Ansari et al., 2008; Kumar and Venkatesan, 2005). Yet these effects may vary across product categories (Kushwaha and Shankar, 2013) and depend on the specific benefits that the new channel provides (Bell et al., 2018; Melis et al., 2016). In grocery retailing, habitual purchasing and the mix of hedonic and functional goods make long-term behavioral shifts particularly uncertain. Studies suggest that online channels enhance shopping utility for certain categories (e.g., bulky or heavy items that are convenient to order online) but reduce it for products requiring physical inspection or freshness evaluation (Campo and Breugelmans, 2015; Campo, Lamey, et al., 2020). However, less is known about whether these category-specific effects persist or attenuate over time.

To address this gap, our study builds on the theory of shopping utility maximization, which posits that consumers choose purchase patterns that yield the highest total utility. Shopping utility comprises two components: acquisition utility, referring to the benefits of the products offered (e.g., price and assortment), and transaction utility, referring to the convenience and effort associated with obtaining them (e.g., ordering and delivery). In this context, the retailer offered identical prices and assortments across channels, keeping acquisition utility constant. Differences in transaction utility therefore drive observed behavioral changes. The framework links three levels of outcomes: (a) category-level effects driven by perceived online ordering convenience, delivery convenience, and ordering risk; (b) customer-level effects on shopping frequency and monetary value; (c) retailer-level effects on total revenue.

The empirical analysis uses loyalty card data from a Nordic grocery retailer that launched an online channel in late 2015. The sample follows 578 households over a five-year period, including both adopters and non-adopters of the online channel. To identify long-term effects, the study applies a DiD design combined with PSM. It compares purchasing behavior before and after adoption while controlling for self-selection and customer heterogeneity.

The results show that the long-term effects of adoption are consistent with our theoretical framework. Customers who adopted the online channel spent more in product categories that offered high delivery convenience (e.g., bulky or heavy products) and spent less in sensory categories associated with higher perceived online purchase risk. In contrast, purchases of categories associated with online ordering convenience showed no significant long-term change. At the customer level, shopping frequency remained broadly stable while the average monetary value per purchase increased over time. These changes led to higher total expenditure among adopters, indicating higher long-term revenue for the retailer.

This study extends previous research on multichannel retailing by providing empirical evidence on the long-term effects of online channel adoption across category, customer, and retailer outcomes. It also illustrates how a framework based on shopping utility maximization can help retailers analyze influences of digital channel adoption on customer value over time.

4.4. Study 4

How Did COVID-19 Affect Playlist Followers on Spotify?
Authorship: Tanetpong Choungprayoon (Stockholm School of Economics), Hannes Datta (Tilburg University), and Max Pachali (Tilburg University)
Status: Unpublished manuscript. An earlier draft was presented at Economics of the Music Industry in 2022.
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The COVID-19 pandemic reshaped how music was consumed and discovered, particularly on digital platforms where playlists have a central role in promoting track consumption. This study investigates how follower dynamics on Spotify playlists changed during the pandemic. The focus is on curator identity, playlist popularity, and share of major-label tracks. The purpose is to assess how an external disruption affected engagement and the distribution of visibility among stakeholders operating within a platform-controlled environment.

Previous research has shown that playlists have a central role in shaping music discovery and consumption on streaming platforms (Aguiar and Waldfogel, 2018; Datta, Knox, et al., 2018). However, most existing evidence comes from periods of normal platform activity, and this limits understanding of how engagement patterns shift when external shocks disrupt user routines. Our study addresses the limit by examining how playlist follower growth responded to the pandemic. It offers insight on how platform exposure and curator outcomes evolved under disruption.

The study investigates these issues through four empirical questions related to overall follower changes, playlist popularity, curator type, and share of major-label tracks within playlists. Together, these questions assess whether engagement during the pandemic became (a) more concentrated among dominant stakeholders or (b) more broadly distributed across the platform.

The empirical analysis uses playlist-level data from Spotify, collected through third-party sources including Chartmetric for follower information and Every Noise at Once for playlist featuring indicators. The final sample, covering periods before and after the pandemic was declared, includes 39,918 active playlists tracked weekly from October 2019 to October 2020. Focusing on within-playlist variation, the empirical strategy employs a unit fixed effects model to estimate how playlist followers changed before and after the pandemic onset. This approach controls for persistent playlist characteristics (e.g., genre, theme, long-run popularity) while measuring the effect of time-varying pandemic indicators. Three complementary measures are used: a binary indicator for the pandemic declaration, a country-weighted government Stringency Index capturing the intensity of restrictions, and a country-weighted measure of residential mobility capturing changes in time spent at home.

The study also examines heterogeneous effects across playlists. Playlists are categorized into five popularity tiers based on follower percentiles, allowing the analysis to compare highly popular "superstar" playlists with mid-tail and long-tail playlists. In addition, playlists are classified according to curator type, including Spotify, major labels, independent labels, artists, professional curators, and users. Finally, the analysis considers the share of tracks from major record labels within each playlist to evaluate whether established industry content influenced follower growth during the pandemic.

The results show that there was no significant change in average follower growth following the pandemic declaration. However, an increase in follower growth when government restrictions intensified and users spent more time at home suggests that playlist engagement responded more to behavioral changes than to the declaration itself. The effects also differed across playlists. Mid-tail and long-tail playlists experienced relatively stronger growth compared to the most popular superstar playlists, indicating a broader distribution of engagement across content. Spotify-curated playlists were more resilient than those curated by other stakeholders and showed stronger follower growth particularly among mid-tail and long-tail playlists. Playlists with higher shares of major-label tracks showed some positive association with follower growth, but this effect was relatively small once track-level popularity was taken into account.

These findings demonstrate how large-scale disruptions can reshape engagement patterns on digital platforms. During the pandemic, follower growth became less concentrated among the most popular playlists, yet platform-curated playlists maintained a strong position within the ecosystem. The results highlight the role of platform governance, curator resources, and content composition in shaping visibility and engagement on streaming platforms across periods of external disruption.

Chapter 5

Discussion and Future Directions

In this final chapter, I step back from the specifics of each study to reflect more broadly on what the thesis contributes. The specific contribution from each separate study is outlined in the corresponding article (see the appended articles, Articles 1–4). The sections that follow are organized into four sections describing theoretical contributions, managerial implications, methodological notes, and limitations (with directions for future research). Each section connects insights across the empirical studies to identify recurring patterns and broader lessons that extend beyond the individual analyses. Across these sections, the chapter provides an integrated synthesis of the thesis's main contributions and outlines directions for future research.

5.1. Theoretical Contributions

This thesis contributes to marketing and retail theory by demonstrating how large-scale behavioral data, when analyzed through established consumer behavior theories, can be used to examine how strategic decisions relate to customer responses across different retail settings. Following a consumer-based strategy perspective, which emphasizes the use of insights from customer behavior to inform strategic decisions (Hamilton, 2016), the studies treat observable customer responses as the unit of analysis. These responses provide a behavioral basis for assessing how strategic decisions play out across contexts, rather than interpreting outcomes in isolation.

First, this thesis highlights the importance of retail context when evaluating the strategies' effectiveness. Across Studies 1–4, results illustrate that customer responses to retail strategies are not consistent across formats, brands, channels, and platform participants. Studies 1 and 2 show that, even within the same retailer, the impact of pricing strategies and discounts for PL products cannot be generalized. Price elasticities and profit outcomes differ systematically by store format, PL tier, and product category. These findings align with prior research on multiformat retailing and PLs (e.g., Geyskens et al., 2010; Haans and Gijsbrechts, 2011), and with broader evidence on variations in marketing mix across formats (Wichmann, Uppal, et al., 2021). They also suggest that performance should not be evaluated using aggregated effects alone, but must account for differences across context, brand, and assortment. Study 4 extends this context principle to digital platforms to reveal that Spotify's playlist follower dynamics during the pandemic did not follow uniform patterns but differed by curator type and content composition. It further shows that, consistent with broader platform dynamics, external shocks can shift visibility and outcomes unevenly across platform participants (Wichmann, Wiegand, et al., 2022).

Second, the studies jointly demonstrate that customer responses help explain how strategic actions translate into observable outcomes. Rather than presenting outcomes without explanation, each study links strategic actions (e.g., pricing, channel introduction, and platform management) to customer responses in purchasing or platform interaction. For example, Study 3 draws on shopping utility maximization to explain why online channel introduction for a grocery context altered the mix and monetary value of purchases over time. The study expands on work by Campo and Breugelmans (2015) and Melis et al. (2016), and it aligns with recent evidence on household adaptation to economic pressures and category-level adjustments (Scholdra et al., 2022). It shows that long-term revenue changes are driven by persistent shifts in the categories from which customers purchase. In particular, customers increase spending in categories with higher online delivery convenience, and this leads to higher value per visit over time. Study 4, in turn, shows that customer behavior on digital platforms reflects broader shifts in daily routines during COVID-19. As time spent at home increased, users adjusted their listening behavior, leading to changes in how attention was distributed across playlists. These patterns are more clearly understood when observed behavior is interpreted in relation to external conditions.

Third, the thesis refines existing knowledge on pricing and channel strategies. Through comparison of regular price changes, temporary discounts, and PL tiers, in Studies 1 and 2 the findings show that neither price nor discount elasticity is consistent across products and store formats. For example, Study 2 shows that discount responsiveness is stronger in hypermarkets than in smaller formats. Study 1 further shows that profitability differs across PL tiers depending on store format. These results build on previous findings (e.g., Ailawadi, Harlam, et al., 2006; Shankar and Krishnamurthi, 1996; Widdecke et al., 2022) and highlight that the effectiveness of pricing strategies depends on both store format and assortment structure. Study 3 similarly shows that the effects of online channel adoption on long-term value are not uniform but dependent on how customers adjust their purchasing behavior over time.

Last, the thesis emphasizes both the value and the limits of data-driven approaches. By leveraging unique retailer and platform datasets that directly connect strategy to observed behavior, the studies show that insights do not come from data volume alone but from how data are interpreted. Common generalizations, such as the belief that discounting always increases sales, or that online channels always add value, are shown to depend on context. The thesis therefore substantiates calls for theory-driven, context-aware analytics (Dekimpe, 2020), echoing similar arguments for more adaptive, context-specific decisions on marketing mix (Wichmann, Uppal, et al., 2021). It suggests a model for future research that balances prediction with explanation.

5.2. Managerial Implications

Many of the findings in this thesis are not new to practitioners. Price and discounting are not the same thing. Store formats influence how customers behave. Platforms tend to favor their own content. However, the issue is that these insights are not often reflected in how decisions are actually implemented or evaluated in practice. As noted by McKinsey & Company (2021), performance reports often aggregate prices and promotions under a single pricing which obscures their distinct effects. Store formats have traditionally been treated primarily as alternative offering channels, not as distinct behavioral contexts. Recent industry reports (e.g., Accenture, 2024; Bain & Company, 2025) suggest that retailers are beginning to rethink this view.

The contribution of this thesis is therefore not to introduce new ideas but to quantify and structurally outline what is already known. By testing these differences across formats, categories, and time, the studies show where common assumptions hold and where they do not. In particular, they show that applying the same strategy across contexts can lead to very different outcomes. This is consistent with prior work showing that managerial insights are more useful when grounded in real-world data and linked to practical decisions (Schauerte et al., 2023).

Take, for instance, the idea that deep discounts drive sales. This is generally true, but the effect could depend on format, product category, and timing. Studies 1 and 2 show that profit gains from price increases on budget PLs hold in hypermarkets but not in supermarkets. Promotion fatigue also varies across categories, and customers' past exposure to discounts reduces discounts' future effectiveness. These findings are not new, but they are rarely quantified or compared across formats, categories, and customer groups. The key implication is not simply that discounts work or that formats matter, but that applying the same pricing approach across products, formats, or customer groups can lead to suboptimal outcomes. Managers therefore need to be more precise in how they frame and evaluate pricing decisions.

In place of such broad advice as "be agile" or "embrace personalization" (advice often found in industry reports; e.g., Accenture, 2024; McKinsey & Company, 2019), by quantifying effects across formats, categories, and time this thesis shows where differences actually matter. The findings are based on observed customer behavior in real empirical settings, and they demonstrate that practical improvements come from making more precise and structured use of existing data.

This thesis also challenges the common assumption that more data will necessarily improve decision-making. Retailers and platforms already have access to large amounts of data, yet the main challenge often lies in how that data is interpreted. Across the studies, better insights are not driven by larger datasets but by framing decisions through consumer behavior theory (e.g., in terms of utility, perceived value, or platform structure). In this sense, theory can serve as a practical tool for interpreting observed patterns, especially when data are noisy or incomplete. Understanding customer behavior—grasping why customers switch channels, respond to price changes, or interact with content—may be more transferable than relying solely on additional data or tools. This does not imply that data are unimportant, but it does imply that more data alone may not always lead to better decisions.

Further, this thesis contributes is its attention to time. In practice, for example in campaign planning, time is often treated as an operational detail rather than as part of how decisions are made. Across the four studies, the results show that the duration of effects, their persistence over time, is just as important as the effects themselves. Study 1 distinguishes between short- and long-run price responses. Study 3 tracks how customer behavior changes after online channel adoption and which of these changes persist over time. Study 4 examines how follower patterns shift in response to a system-wide disruption. These analyses focus on more concrete questions: what persists, for whom, and for how long? By treating time as part of the analysis, not only as a reporting interval, the thesis highlights how effects can build, fade, or change over time.

Finally, while the studies are empirically grounded in grocery retail and music streaming, their implications extend beyond these settings. The findings from multiformat pricing and multichannel allocation are relevant for other frequently purchased categories such as health, household goods, or personal care. Similarly, the results on platform behavior apply not only to Spotify but also to retail environments that manage digital visibility through search results, home page placements, and recommendation systems. What matters is not the domain but how format, price, assortment, and customer decision-making interact. These interactions are not industry-specific; they arise whenever businesses manage what customers see and how they choose across formats and channels.

5.3. Methodological Notes

Throughout this thesis, theory serves as a guide in shaping the empirical approach. The choice of variables, model structures, and empirical specifications are all grounded in prior research to ensure that the results speak to meaningful constructs in retail strategy and consumer behavior. In particular, each study connects theoretical findings to measurable and observable outcomes (e.g., how price changes affect sales and profit, how channel adoption changes purchasing behavior, or how platform exposure relates to follower dynamics). This helps ensure that the empirical results remain connected to meaningful managerial questions.

A recurring methodological consideration across the studies is the use of panel data structures that support analysis of customer behaviors' change over time. This thesis uses three complementary empirical strategies depending on the level of decision: error-correction modeling (ECM) for pricing responses, DiD for channel adoption, and panel fixed effects models for platform behavior. These approaches are used not only to control for unobserved differences but also to capture how effects evolve over time. Panel data enables examination of 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 treated in the course of the analysis. In Studies 1 and 2, ECM separates short-term effects from longer-term adjustments in sales and profits (Pauwels et al., 2007). Study 3, comparing pre- and post-periods between matched customer groups, uses a DiD design to track sustained behavioral changes after digital channel adoption (Golder et al., 2022). Study 4 applies fixed effects panel models with time controls to isolate change while accounting for shocks related to the COVID-19 pandemic. Across all four studies, these methods allow the analyses to identify whether effects are short-lived or persistent, and how they develop over time. This is consistent with prior research emphasizing that consumer behavior is dynamic and should be analyzed over time (Zhang and Chang, 2021).

Another important aspect of the methodological approach is the use of real-world data from retailers and digital platforms. This thesis prioritizes high external validity by studying actual observed customer behavior in real decision environments. Across all studies, efforts were made to account for unobserved heterogeneity, to control for confounding factors, and to use robust estimation techniques. The first study applies ECM to estimate both short- and long-term price effects across PL tiers and formats; it thereby links sales responses to profit outcomes. The second study uses a sequential 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 PSM to estimate long-term behavioral changes following online channel adoption. The fourth study, leveraging government restriction indices and mobility data to contextualize pandemic effects uses a unit fixed effects panel model to assess changes in playlist followers over time. These designs reflect the shared goal of extracting credible insights from observational data while acknowledging its boundaries. This design aligns with recent calls for an empirics-first approach, where theory generation is grounded in the systematic analysis of real-world behavioral data, not imposed a priori (Golder et al., 2022).

What ties the empirical studies together is the effort to link observed behavioral outcomes such as purchasing responses, channel adoption, and follower changes to broader retailer-level outcomes. This approach reflects the belief that meaningful analysis is derived not from statistical complexity alone but from efforts to build 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 PL tiers. In the online channel adoption study, the analysis goes from product mix shifts to sustained revenue differences. In the platform study, follower changes are used as observable indicators of exposure and response. This ensures that the analysis remains relevant for understanding performance outcomes.

Finally, the studies follow a consistent structure from theory to empirical specification and interpretation. Each study starts from a theoretical framework to guide the choice of variables and model specification. The empirical results are then interpreted in light of these theoretical expectations. This structure helps maintain comparability across contexts, and it ensures that the analysis remains grounded in both theory and observed behavior. Using established methods with real-world data strengthens the validity of the results and supports their practical relevance.

5.4. Limitations and Future Directions

Like all empirical research, this thesis is shaped by constraints in data, scope, and method. Recognizing these limitations is important, not only for the validity of the current findings but also for guiding future research that builds on and improves them. While each empirical study has its own specific boundaries, several overarching themes emerge across the thesis. These include contextual scope, modeling constraints, and data design and inference.

All four studies are embedded in specific retail and platform environments. While this enhances the real-world relevance of the findings, it also constrains their generalizability beyond the studied contexts. The pricing analyses (Studies 1 and 2) rely on data from a single Nordic grocery retailer where loyalty norms, assortment structures, and competitive intensity may differ from what is found in other markets. Similarly, while the online channel study (Study 3) is situated in an early-adoption setting, the platform analysis (Study 4) focuses on a single period of pandemic disruption. These contextual boundaries invite replication across other geographies, sectors, and timeframes to test the robustness of the patterns identified here. Future research could extend the framework to new categories or retail systems to examine whether the interaction between context, strategy, and consumer response persists under different market conditions (Gielens and Steenkamp, 2019).

A second set of limitations concerns the focus and operationalization of key constructs. The pricing studies isolate regular price and discount effects but do not include such other marketing instruments as in-store displays, advertising, and supplier promotions (Bijmolt et al., 2005; Nijs et al., 2001). This simplification allows for clean estimation of price responsiveness but may understate the joint influence from other marketing actions. In the online channel study, the quasi-experimental design captures behavioral outcomes following adoption, but it simplifies the adoption process itself. Channel adoption is modeled as a discrete event by abstracting from managerial interventions (e.g., communication campaigns or delivery incentives) that might influence both the likelihood and intensity of adoption. Moreover, the focus on grocery purchases, with their unique delivery constraints and purchase rhythms, limits the generalizability of behavioral patterns to other product or service categories (Campo, Lamey, et al., 2020; Kushwaha and Shankar, 2013). Finally, the platform study uses playlist followers as a proxy for engagement, an approach that captures visibility and attention but not actual consumption or revenue outcomes. Together, these modeling constraints highlight a trade-off between analytical clarity and strategic completeness. Future research should address this gap by integrating richer managerial, cost, and behavioral data to achieve a more comprehensive understanding of performance outcomes.

A final limitation stems from reliance on observational data. The quasi-experimental design of Study 3 and the fixed effects approach in Study 4 strengthen causal interpretation but cannot fully eliminate unobserved heterogeneity or selection bias (Goldfarb et al., 2022). Early adopters may differ systematically from non-adopters in ways that are difficult to observe, from digital literacy to risk tolerance and time constraints, which can influence both their likelihood of adoption and their subsequent purchasing behavior (Avery et al., 2012; Li, Konuş, et al., 2015; Rietveld and Eggers, 2018). Similarly, playlist performance may reflect algorithmic or editorial choices that, made by the platform, are not visible to researchers and make it challenging to disentangle organic audience behavior from platform-driven amplification. 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. Future research could combine field experiments, A/B testing, and simulation-based methods with observational data to more directly examine the underlying behavioral processes that cannot be observed in the current data. Integrating survey-based or qualitative insights could also reveal psychological mechanisms behind the behavioral patterns observed.

Overall, the limitations identified in this thesis highlight opportunities for future research. Addressing these through broader contexts, richer data, and complementary methods would help strengthen and extend the insights developed here.

Epilogue

Having highlighted in Chapter 5 what this thesis contributes to theory, practice, and methodology, I cannot help but feel a little strange writing about such contributions as if they belonged in separate boxes. This reflection is not meant to be generalizable, and it would certainly fail an external validity test. Then again, it's meant as reflection, not replication. I reflect that none of these insights came from pursuing any contribution in isolation. Over five years of sweat and tears, I realized that they came from a messy, nonlinear process. Sometimes they came accidentally, sometimes intentionally, but most of the time procedurally. This is because the process by which I arrived at the contributions was a process made up of cycles. The cycles involved understanding the data, making sense of them, recognizing limitations, building visual tools, refining models, and then interpreting the results and the story they seemed to tell.

To make sense of anything, I first had to understand the data—not just statistically, but structurally and contextually. What did each variable represent? What patterns were already there before I started drawing lines through the data or asking algorithms to discover them for me? What was missing, why, and what could be done about it? These questions became the starting point for every project. And just as much as theory guides analysis, the data often forced me to revisit assumptions and rethink the questions I was asking. Eventually, I learned to ask better questions, shifting from "Is this effect significant?" to "What does this tell us about how people behave (or don't) in certain situations, and about how businesses respond?"

Throughout my studies, some of the most striking insights did not come from rigorous models or perfect specifications. And by striking, I don't mean the most statistically robust. Those came later, after the models were built and the story had already been laid out. The real insights came while exploring data through interactive dashboards that I designed myself. They allowed me to visualize patterns, compare segments, and trace how key variables evolved over time through colors, shapes, and simple interactive elements such as filters and dropdowns. No hypothesis tests, no coefficients; just time series, simple cohort comparisons, and a thousand tabs open at once.

These tools were not merely exploratory. They suggestively pointed toward observed patterns. They didn't prove the patterns, and working with them was less about analyzing the data, more about narrating it, about trying to see where meaning might be hiding. It felt like holding a book of theory in the dark, with the dashboard offering just enough light to read a few lines at a time. Some might say it's enough to read in the dark, if you just focus hard enough. Others might say it's all about finding the light and seeing what appears. But I think I prefer a little light to guide the reading.

Looking back on this process, I have come to realize that research in the social sciences 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 is about knowing when to zoom in on a variable and when to step back and ask if that variable matters at all. The research I conducted became less a process of control and more a negotiation with the data, the related literature, and my own assumptions. And while some might prefer to treat assumptions as something objective or at least external to the researcher, I've learned that they are anything but. They shape what we see, what we ignore, and what we are willing to believe the data is telling us.

Part of the reason I came to see research this way is that this thesis took long enough for me to spend some time in industry. The more I moved between the two (full time at the bank and part time at the PhD office), the stranger it felt to hear people talk about academia versus industry as if they constituted different worlds. From my experience, the academic process is almost identical to the industry process. Both try to make sense of observed behavior, to predict outcomes and improve decisions, whether through behavioral explanations or algorithmic models. The only real difference is emphasis. Academia polishes its explanations until they are publishable. Industry polishes its tools until they are profitable. One asks what is going on and why. The other asks what to do next. Both chase relevance, each through a different lens: the microscope of academia and the binoculars of industry.

That said, I can't resist a confession.

Sometimes I wonder if social science has (or will) become a full-blown circus of triviality. Everyone's performing, juggling regressions, walking the tightrope of robustness checks, and pulling contributions out of hats. We spend years polishing results so safe, so painfully obvious, that any trace of something even slightly interesting is lost under layers of statistical rigor. Then comes the best part: we frame the findings in terms of what they add to the literature, even though it always remains the same literature, in the same journals, read by the same people. As if the point of research were not to understand the world but to impress insiders. 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 not always 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 isn't running its own sideshow. If academia is a circus of triviality, then industry is a magic show of illusory certainty, of quick solutions pulled out of black box algorithms, of KPIs waved like proof of wisdom, of ambiguity made to disappear behind convincing tables and dashboards. Industry frames impact but fears uncertainty, celebrates innovation but avoids reflection. The costumes differ, but the performance is the same: a pursuit of efficiency over understanding, staged according to the same 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. People in industry do not need to be told context matters; they live in it. They do not theorize about heterogeneity; they market to it. And maybe, just maybe, good research is not the kind that holds itself apart from practice. Maybe it's the kind that builds practice from tools, constraints, and theory, lit by a dashboard like the one that sparked every idea in this thesis.

References

Accenture (2024). *Reinventing the future of retail*. en. https://www.accenture.com/us-en/insights/retail/reinventing-future-retail. Accessed: 2025-10-16.

Aguiar, L. and J. Waldfogel (2018). "Platforms, Promotion, and Product Discovery: Evidence from Spotify Playlists." In: Working Paper Series 24713.

Aguiar, L., J. Waldfogel, and S. Waldfogel (2021). "Playlisting favorites: Measuring platform bias in the music industry." In: *Int. J. Ind Organiz* 78, p. 102765.

Ailawadi, K. L., K. Pauwels, and J.-B. E. M. Steenkamp (2008). "Private-label use and store loyalty." In: *Journal of*.

Ailawadi, K. L. and B. Harlam (2004). "An Empirical Analysis of the Determinants of Retail Margins: The Role of Store-Brand Share." In: *J. Mark.* 68.1, pp. 147–165.

Ailawadi, K. L., B. A. Harlam, J. César, and D. Trounce (2006). "Promotion profitability for a retailer: The role of promotion, brand, category, and store characteristics." In: *J. Mark. Res.* 43.4, pp. 518–535.

Anderson, C. (2006). *The Long Tail: Why the Future of Business Is Selling Less of More*. en. Hachette UK.

Ansari, A., C. F. Mela, and S. A. Neslin (2008). "Customer channel migration." In: *J. Mark. Res.* 45.1, pp. 60–75.

Avery, J., T. J. Steenburgh, J. Deighton, and M. Caravella (2012). "Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time." In: *J. Mark.* 76.3, pp. 96–111.

Bain & Company (2025). *The future of retail: Six disruptions that could shape the next decade*. en. https://www.bain.com/insights/the-future-of-retail-six-disruptions-that-could-shape-the-next-decade/. Accessed: 2025-10-16.

Baker, J., A. Parasuraman, D. Grewal, and G. B. Voss (2002). "The influence of multiple store environment cues on perceived merchandise value and patronage intentions." en. In: *J. Mark.* 66.2, pp. 120–141.

Bar-Isaac, H., G. Caruana, and V. Cuñat (2012). "Search, Design, and Market Structure." In: *Am. Econ. Rev.* 102.2, pp. 1140–1160.

Bell, D. R., S. Gallino, and A. Moreno (2018). "Offline showrooms in omnichannel retail: Demand and operational benefits." In: *Manage. Sci.* 64.4, pp. 1629–1651.

Bijmolt, T. H. A., H. J. van Heerde, and R. G. M. Pieters (2005). "New Empirical Generalizations on the Determinants of Price Elasticity." In: *J. Mark. Res.* 42.2, pp. 141–156.

Bilgicer, T., K. Jedidi, D. R. Lehmann, and S. A. Neslin (2015). "Social Contagion and Customer Adoption of New Sales Channels." In: *J. Retail.* 91.2, pp. 254–271.

Boehm, M. (2008). "Determining the impact of internet channel use on a customer's lifetime." In: *Journal of Interactive Marketing* 22.3, pp. 2–22.

Bonfrer, A., P. Chintagunta, and S. Dhar (2022). "Retail store formats, competition and shopper behavior: A Systematic review." In: *J. Retail.* 98.1, pp. 71–91.

Bradlow, E. T., M. Gangwar, P. Kopalle, and S. Voleti (2017). "The Role of Big Data and Predictive Analytics in Retailing." In: *J. Retail.* 93.1, pp. 79–95.

Breugelmans, E. et al. (2023). "The Future of Physical Stores: Creating Reasons for Customers to Visit." In: *J. Retail.*

Brynjolfsson, E., Y. (Hu, and M. D. Smith (2010). "Research Commentary— Long Tails vs. Superstars: The Effect of Information Technology on Product Variety and Sales Concentration Patterns." In: *Information Systems Research* 21.4, pp. 736–747.

Campo, K. and E. Breugelmans (2015). "Buying Groceries in Brick and Click Stores: Category Allocation Decisions and the Moderating Effect of Online Buying Experience." In: *Journal of Interactive Marketing* 31, pp. 63–78.

Campo, K., L. Lamey, E. Breugelmans, and K. Melis (2020). "Going Online for Groceries: Drivers of Category-Level Share of Wallet Expansion." In: *J. Retail.*

Chintala, S. C., J. Liaukonytė, and N. Yang (2023). "Browsing the Aisles or Browsing the App? How Online Grocery Shopping is Changing What We Buy." In: *Marketing Science*.

Cui, T. H. et al. (2021). "Informational Challenges in Omnichannel Marketing: Remedies and Future Research." In: *J. Mark.* 85.1, pp. 103–120.

Datta, H., G. Knox, and B. J. Bronnenberg (2018). “Changing their tune: How consumers’ adoption of online streaming affects music consumption and discovery.” In: *Marketing Science*.

Datta, H., H. J. van Heerde, M. G. Dekimpe, and J.-B. E. M. Steenkamp (2022). *Cross-National Differences in Market Response: Line-Length, Price, and Distribution Elasticities in 14 Indo-Pacific Rim Economies*.

Dekimpe, M. G. (2020). “Retailing and retailing research in the age of big data analytics.” In: *International Journal of Research in Marketing* 37.1, pp. 3–14.

DelVecchio, D., D. H. Henard, and T. H. Freling (2006). “The effect of sales promotion on post-promotion brand preference: A meta-analysis.” In: *J. Retail.* 82.3, pp. 203–213.

Denk, J., A. Burmester, M. Kandziora, and M. Clement (2022). *The impact of COVID-19 on music consumption and music spending*.

Dhar, S. K., S. J. Hoch, and N. Kumar (2001). “Effective category management depends on the role of the category.” In: *J. Retail.*

Donovan, R., R. John, M. Gilian, and N. Andrew (1994). “Store atmosphere and purchasing behavior.” In: *J. Retail.* 70.3, pp. 283–294.

Forbes (2024). *From seller to support partner: Retail’s role in catering to shopper segments*. en. `https://www.forbes.com/councils/forbesbusinesscouncil/2024/11/14/from-seller-to-support-partner-retails-role-in-catering-to-shopper-segments/`. Accessed: 2025-10-26.

Gai, P. J. and A.-K. Klesse (2019). “Making recommendations more effective through framings: Impacts of user- versus item-based framings on recommendation click-throughs.” en. In: *J. Mark.* 83.6, pp. 61–75.

Gauri, D. K. et al. (2021). “Evolution of retail formats: Past, present, and future.” en. In: *J. Retail.* 97.1, pp. 42–61.

Gensler, S., M. G. Dekimpe, and B. Skiera (2007). “Evaluating channel performance in multi-channel environments.” In: *Journal of Retailing and Consumer Services* 14.1, pp. 17–23.

Geyskens, I., K. Gielens, and E. Gijsbrechts (2010). “Proliferating Private-Label Portfolios: How Introducing Economy and Premium Private Labels Influences Brand Choice.” In: *J. Mark. Res.* 47.5, pp. 791–807.

Gielens, K. and J.-B. E. M. Steenkamp (2019). “Branding in the era of digital (dis)intermediation.” In: *International Journal of Research in Marketing* 36.3, pp. 367–384.

Gielens, K. and J.-B. E. M. Steenkamp (2025). "EXPRESS: An investigation into the evolution of marketing mix effectiveness: An Empirics-First approach." en. In: *J. Mark.* 00222429251412261.

Golder, P. N. et al. (2022). "Learning from Data: An Empirics-First Approach to Relevant Knowledge Generation." In: *J. Mark.*

Goldfarb, A., C. Tucker, and Y. Wang (2022). "Conducting Research in Marketing with Quasi-Experiments." In: *J. Mark.* 86.3, pp. 1–20.

Guyt, J. Y., H. Datta, and J. Boegershausen (2024). "Unlocking the potential of web data for retailing research." en. In: *J. Retail.*

Haans, H. and E. Gijsbrechts (2011). ""One-deal-fits-all?" On Category Sales Promotion Effectiveness in Smaller versus Larger Supermarkets." In: *J. Retail.* 87.4, pp. 427–443.

Hamilton, R. (2016). "Consumer-based strategy: using multiple methods to generate consumer insights that inform strategy." en. In: *J. Acad. Mark. Sci.* 44.3, pp. 281–285.

Hamilton, R. and A. Chernev (2013). "Low Prices are Just the Beginning: Price Image in Retail Management." In: *J. Mark.* 77.6, pp. 1–20.

Hanssens, D. M. and K. H. Pauwels (2016). "Demonstrating the value of marketing." In: *J. Mark.* 80.6, pp. 173–190.

Jürgensmeier, L. and B. Skiera (2025). "EXPRESS: Measuring self-preferencing on digital platforms." en. In: *J. Mark.* 00222429251360772.

Keller, K. O., M. G. Dekimpe, and I. Geyskens (2022). "Adding budget and premium private labels to standard private labels: Established empirical generalizations, emerging empirical insights, and future research." In: *J. Retail.* 98.1, pp. 5–23.

Keller, K. O., I. Geyskens, and M. G. Dekimpe (2020). "Opening the umbrella: The effects of rebranding multiple category-specific private-label brands to one umbrella brand." en. In: *J. Mark. Res.* 57.4, pp. 677–694.

Keller, K. O. and R. Sethuraman (2026). "Promotion elasticities of national and store brands: The effect of price level and brand type on promotion elasticity." en. In: *J. Retail.*

Konuş, U., P. C. Verhoef, and S. A. Neslin (2008). "Multichannel Shopper Segments and Their Covariates." In: *J. Retail.* 84.4, pp. 398–413.

KPMG (2025). *From data overload to data-driven decisions in retail*. en. `https://kpmg.com/us/en/articles/2025/from-data-overload-driven-decisions.html`. Accessed: 2025-10-15.

Kumar, V. and R. Venkatesan (2005). “Who are the multichannel shoppers and how do they perform?: Correlates of multichannel shopping behavior.” In: *Journal of Interactive Marketing* 19.2, pp. 44–62.

Kushwaha, T. and V. Shankar (2013). “Are multichannel customers really more valuable? the moderating role of product category characteristics.” In: *J. Mark.* 77.4, pp. 67–85.

Lalwani, A. K. and K. B. Monroe (2005). “A Reexamination of Frequency-Depth Effects in Consumer Price Judgments.” en. In: *J. Consum. Res.* 32.3, pp. 480–485.

Leeflang, P. S. H., J. E. Wieringa, T. H. A. Bijmolt, and K. H. Pauwels (2014). *Modeling Markets*. Springer New York.

Lemon, K. N. and P. C. Verhoef (2016). “Understanding customer experience throughout the customer journey.” en. In: *J. Mark.* 80.6, pp. 69–96.

Li, J., U. Konuş, K. Pauwels, and F. Langerak (2015). “The Hare and the Tortoise: Do Earlier Adopters of Online Channels Purchase More?” In: *J. Retail.* 91.2, pp. 289–308.

Li, K. T. and C. Van den Bulte (2023). “Augmented difference-in-differences.” In: *Marketing Science*.

Mazumdar, T., S. P. Raj, and I. Sinha (2005). “Reference price research: Review and propositions.” In: *J. Mark.*

McKinsey & Company (2019). *The ever-changing store: Taking an agile, customer-centric approach to format redesign*. en. `https://www.mckinsey.com/industries/retail/our-insights/the-ever-changing-store-taking-an-agile-customer-centric-approach-to-format-redesign#/`. Accessed: 2025-10-26.

McKinsey & Company (2021). *Pricing and promotions: The analytics opportunity*. `https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/pricing-and-promotions-the-analytics-opportunity#/`.

McKinsey & Company (2025). *State of the Consumer 2025: When disruption becomes permanent*. `https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/state-of-consumer#/`.

Melis, K., K. Campo, L. Lamey, and E. Breugelmans (2016). “A Bigger Slice of the Multichannel Grocery Pie: When Does Consumers’ Online Channel Use Expand Retailers’ Share of Wallet?” In: *J. Retail.* 92.3, pp. 268–286.

Neslin, S. A., D. Grewal, et al. (2006). “Challenges and Opportunities in Multichannel Customer Management.” In: *J. Serv. Res.* 9.2, pp. 95–112.

Neslin, S. A. and V. Shankar (2009). "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions." In: *Journal of Interactive Marketing* 23.1, pp. 70–81.

Nijs, V. R., M. G. Dekimpe, J. B. E. M. Steenkamp, and D. M. Hanssens (2001). "The category-demand effects of price promotions." In: *Marketing Science*.

Osuna, I., J. González, and M. Capizzani (2016). "Which Categories and Brands to Promote with Targeted Coupons to Reward and to Develop Customers in Supermarkets." In: *J. Retail.* 92.2, pp. 236–251.

Pachali, M. J. and H. Datta (2025). "What drives demand for playlists on Spotify?" en. In: *Mark. Sci.* 44.1, pp. 54–64.

Papies, D., P. Ebbes, and E. M. Feit (2022). "Endogeneity and Causal Inference in Marketing." In.

Pauwels, K., S. Srinivasan, and P. H. Franses (2007). "When Do Price Thresholds Matter in Retail Categories?" In: *Marketing Science* 26.1, pp. 83–100.

Raju, J. S. (1992). "The Effect of Price Promotions on Variability in Product Category Sales." In: *Marketing Science*.

Reinartz, W., N. Wiegand, and M. Imschloss (2019). "The impact of digital transformation on the retailing value chain." In: *International Journal of Research in Marketing* 36.3, pp. 350–366.

Rietveld, J. and J. P. Eggers (2018). "Demand Heterogeneity in Platform Markets: Implications for Complementors." In: *Organization Science* 29.2, pp. 304–322.

Rietveld, J. and M. A. Schilling (2021). "Platform Competition: A Systematic and Interdisciplinary Review of the Literature." In: *J. Manage.* 47.6, pp. 1528–1563.

Rietveld, J., M. A. Schilling, and C. Bellavitis (2019). "Platform Strategy: Managing Ecosystem Value Through Selective Promotion of Complements." In: *Organization Science* 30.6, pp. 1232–1251.

Roth, J., P. H. C. Sant'Anna, A. Bilinski, and J. Poe (2023). "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." en. In: *J. Econom.* 235.2, pp. 2218–2244.

Schauerte, N. et al. (2023). "The managerial relevance of marketing science: Properties and genesis." In: *International Journal of Research in Marketing*.

Scholdra, T. P., J. R. K. Wichmann, M. Eisenbeiss, and W. J. Reinartz (2022). "Households Under Economic Change: How Micro- and Macroeconomic Conditions Shape Grocery Shopping Behavior." In: *J. Mark.* 86.4, pp. 95–117.

Shankar, V. and L. Krishnamurthi (1996). "Relating price sensitivity to retailer promotional variables and pricing policy: an empirical analysis." In: *J. Retail.* 72.3, pp. 249–272.

Sim, J., D. Cho, Y. Hwang, and R. Telang (2022). "Frontiers: Virus Shook the Streaming Star: Estimating the COVID-19 Impact on Music Consumption." In: *Marketing Science* 41.1, pp. 19–32.

Smith, M. D. and R. Telang (2016). *Streaming, Sharing, Stealing: Big Data and the Future of Entertainment*. en. MIT Press.

Ter Braak, A., M. G. Dekimpe, and I. Geyskens (2013). "Retailer private-label margins: The role of supplier and quality-tier differentiation." en. In: *J. Mark.* 77.4, pp. 86–103.

Van Heerde, H. J. and M. G. Dekimpe (2024). "Household and retail panel data in retailing research: Time for a renaissance?" In: *J. Retail.*

Van Nierop, J. E. M., P. S. H. Leeflang, M. L. Teerling, and K. R. E. Huizingh (2011). "The impact of the introduction and use of an informational website on offline customer buying behavior." In: *International Journal of Research in Marketing* 28.2, pp. 155–165.

Van Oest, R. (2013). "Why are Consumers Less Loss Averse in Internal than External Reference Prices?" In: *J. Retail.* 89.1, pp. 62–71.

Verhoef, P. C., P. K. Kannan, and J. J. Inman (2015). "From Multi-Channel Retailing to Omni-Channel Retailing. Introduction to the Special Issue on Multi-Channel Retailing." In: *J. Retail.* 91.2, pp. 174–181.

Verhoef, P. C., S. A. Neslin, and B. Vroomen (2007). "Multichannel customer management: Understanding the research-shopper phenomenon." In: *International Journal of Research in Marketing* 24.2, pp. 129–148.

Verhoef, P. C., R. Venkatesan, et al. (2010). "CRM in Data-Rich Multichannel Retailing Environments: A Review and Future Research Directions." In: *Journal of Interactive Marketing* 24.2, pp. 121–137.

Wang, R. J.-H., E. C. Malthouse, and L. Krishnamurthi (2015). "On the Go: How Mobile Shopping Affects Customer Purchase Behavior." In: *J. Retail.* 91.2, pp. 217–234.

Weathers, D., S. D. Swain, and I. Makienko (2015). "When and how should retailers rationalize the size and duration of price discounts?" In: *J. Bus. Res.* 68.12, pp. 2610–2618.

Wichmann, J. R. K., A. Uppal, A. Sharma, and M. G. Dekimpe (2021). "A global perspective on the marketing mix across time and space." In: *International Journal of Research in Marketing*.

Wichmann, J. R. K., N. Wiegand, and W. J. Reinartz (2022). "The Platformization of Brands." In: *J. Mark.* 86.1, pp. 109–131.

Widdecke, K. A., W. I. Y. Keller, K. Gedenk, and B. Deleersnyder (2022). "Drivers of the synergy between price cuts and store flyer advertising at supermarkets and discounters." In: *International Journal of Research in Marketing*.

Wlömert, N., D. Papies, and H. J. van Heerde (2025). "EXPRESS: Driving music demand in the age of streaming: Understanding the heterogeneity in curated playlist effectiveness." en. In: *J. Mark.* 00222429251395986.

Zeithaml, V. A. (1988). "Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence." In: *J. Mark.* 52.3, p. 2.

Zhang, J. Z. and C.-W. Chang (2021). "Consumer dynamics: theories, methods, and emerging directions." In: *Journal of the Academy of Marketing Science* 49.1, pp. 166–196.

Zhang, Y., J. Li, and T. W. Tong (2022). "Platform governance matters: How platform gatekeeping affects knowledge sharing among complementors." en. In: *Strategic Manage. J.* 43.3, pp. 599–626.

The Articles

Article 1

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

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

Tanetpong Choungprayoon †

Abstract

This study examines how pricing affects sales and profitability of multi-tier private labels (PLs) across store formats within a single retail chain. Using scanner data from a Nordic grocery retailer operating hypermarkets, supermarkets, and convenience stores, we estimate error correction models linking price changes to sales and profits for budget, standard, and premium PL tiers. Results show that own-price elasticities are negative for standard and premium tiers, while the budget tier exhibits heterogeneous responses. Cross-tier substitution effects are limited, indicating that PL tiers largely function independently. Profit elasticities are positive across tiers, with format-specific differences: hypermarkets gain most from budget-tier pricing, while supermarkets benefit from standard and premium tiers. The findings demonstrate that pricing effectiveness is tier- and format-specific, highlighting the need for more format-contingent pricing strategies, where the role of each PL tier in pricing decisions varies across retail formats rather than following a uniform approach.

Keywords: Grocery retailing; Private labels; Pricing; Store formats

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1 Introduction

In recent years, a grocery retail landscape has seen a significant shift towards the adoption of private labels (PLs), store brands owned by the retailer, reflecting broader consumer acceptance and retailer strategies. Growing from 31% in 2018 to 38% in 2024, private labels have claimed a significant share of the grocery retail market value in Europe (IRI, 2024). The popularity of private labels is evident not only in hard discount stores but also in traditional supermarkets, illustrating their common appeal across different retail formats (GfK, 2021). Private labels are usually diversified into various tiers such as budget, standard, and premium tiers (Keller et al., 2022). Each tier is tailored to cater to distinct consumer segments and needs. With the growing popularity of private labels, many grocery retail chains tend to offer a tiered assortment across all their stores within a chain. Yet, managing private labels across different store formats is challenging since each format serves different shopping missions and faces operational constraints, such as limited shelf space or assortment depth (e.g. Gauri et al., 2008). Thus, retailers must adapt their multi-tier PL strategies by adjusting pricing and tier emphasis to match the shopping behavior and constraints of each store format. In other words, rather than applying a uniform pricing strategy across all formats, retailers may benefit from placing different pricing emphasis on specific PL tiers depending on the store format. This does not necessarily imply fully localized store-level price differences, but rather format-contingent pricing decisions within a unified pricing system.

Prior research suggests that retailers often maintain relatively uniform prices across stores, despite variation in local demand and competition. This tendency has been attributed to factors such as brand image concerns, consumer perceptions of fairness, and organizational constraints (DellaVigna & Gentzkow, 2019). Moreover, while local price differentiation can improve profitability under certain conditions, uniform pricing may also be optimal when it helps soften competition across markets (Li et al., 2018). As a result, retailers may not fully adjust prices across stores. This makes it important to understand how pricing effectiveness varies across formats and tiers within existing pricing structures. This is particularly relevant for private labels, where retailers have greater control over pricing and can adjust tier-level strategies to align with format-specific objectives.

To design effective pricing strategies for multi-tier PLs across formats, retailers require empirical insights into how price changes affect sales and profitability within each format. While private label tiers are often deployed uniformly across store types, their actual performance may differ. Previous research has extensively examined the impact of introducing different tiers of PLs on brand, category, and store performance (e.g., Geyskens et al., 2010; Gielens, 2012; ter Braak et al., 2013), and how these tiers perform across different types of retail chains (i.e., supermarkets versus discounters) (e.g. Hökelekli et al., 2017). However, there has been limited focus on how multi-tier PLs perform across different store formats within the same retail chain, particularly in terms of their sales–profitability relationship. Prior research tends to examine sales or profitability in isolation, without tracing the chain of effects from price changes to sales to profit.

To address these gaps, this study investigates how multi-tier PLs respond to pricing strategies across physical store formats within the same retailer. Specifically, we examine whether differences in price effectiveness on sales persist across formats and how these differences translate into format-specific profitability. In doing so, we focus on variation in observed prices over time within each store format, rather than comparing static price differences across formats. To do so, we propose a framework that links price changes to sales and then to profit, accounting for both own-tier and cross-tier effects. This framework allows us to isolate substitution patterns among PL tiers and assess whether they function independently, complement one another, or cannibalize sales across tiers. By doing so, we examine not only the responsiveness of each tier to price changes but also the degree to which PL tiers collectively enhance or reduce overall profitability within each store format. This question is not only empirically practical but also responds to the call for future research opportunities proposed by Keller et al. (2022) on understanding retailers' overall profitability with multi-tiered PLs. Understanding how pricing impacts tier-level performance across different store formats provides academic insights into private label portfolio literature and offers actionable guidance for retailers seeking to enhance store-level profitability.

Thus, the purpose of this study is answer the question by empirically examining the effects of pricing on the sales and profits of each tier of private labels across various store formats within the same retail chain. We utilize detailed scanner data available from a Nordic grocery retailer, which operates under three specific store formats including hypermarkets, supermarkets, and convenience stores and offers multi-tier private labels categorized into the budget tier, the standard tier and the premium tier. Our analysis is based on observed transaction prices, which reflect the effective prices paid by consumers and incorporate both regular and promotional pricing. We explore how price adjustments in one tier may influence sales in others, capturing cross-tier responsiveness and identifying whether interactions among tiers reflect substitution, complementarity, or independence. Specifically, we first estimate how changes in the prices of each PL tier affect their respective sales within the same format. We then use these estimated changes in sales to assess how price adjustments consequently impact overall store profitability, isolating the contribution of each tier while accounting for interdependencies across tiers. This step-by-step approach allows us to clearly delineate the direct effects of price changes on sales volume and their subsequent effects on profitability.

Our findings suggest that the performance of multi-tier PLs varies significantly across store formats, both in terms of sales responsiveness and profitability. While standard and premium PL tiers consistently exhibit negative price elasticity, the magnitude of this effect differs across formats, with the hypermarket and the supermarket showing distinct responsiveness. Budget tiers display more heterogeneous patterns, including instances of positive price elasticity, implying varying perceptions of value. Moreover, we find limited evidence of cross-tier substitution, particularly for the premium tier, which shows minimal responsiveness to price changes in lower tiers across most categories and store formats. This suggests that consumers purchasing premium PLs tend to view them as distinct offerings rather than interchangeable with budget or standard alternatives, supporting prior findings that premium products often serve niche or quality-focused segments with weaker substitution tendencies. As a result, pricing decisions within the premium tier may have less impact on broader portfolio dynamics, reinforcing the need for tier-specific strategies. These differences in sales responses translate into divergent profitability outcomes; the hypermarket tends to benefit more from pricing strategies targeting the budget tier, while the supermarket see stronger profit returns from standard and premium tiers. The convenience store exhibits limited pricing variation and restricted cross-tier interactions, reflecting its narrower assortment and targeted format strategy.

In summary, our study demonstrates that the effects of pricing on multi-tier PLs are highly format- and tier-specific. By tracing the link from price changes to both sales and profitability, we show that budget, standard, and premium PLs respond differently across hypermarket, supermarket, and the convenience store. Limited cross-tier price responsiveness suggests that most tiers function independently, enabling retailers to manage each tier with minimal concern for cannibalization. However, in cases where pricing in one tier influences another, particularly between the budget and standard tiers, retailers should carefully evaluate the profitability implications. Our step-by-step approach offers a practical way to quantify how price changes in any given tier impact total store profitability, supporting more informed pricing decisions across the private label portfolio.

The rest of the paper is organized as follows. We provide a brief overview of relevant literature and our research framework that illustrates the relationships among profit, price, cost, and quantity of sales across multi-tier private labels in Section 2. We introduce the empirical setting, data and measure for this study in section 3. We specify our step-by-step approach to delineate the direct effects of price changes on sales volume and their subsequent effects on profit margins in section 4. We present and discuss our results in Section 5 and 6 respectively.

2 Background and Research Framework

2.1 Literature Review

The previous literature on private labels extensively covers their sales performance, profitability, and market segmentation strategies (Table 1). Yet, few studies examine how pricing influences both sales and profitability across multiple PL tiers and store formats within the same retail chain. In particular, the sequential link between price changes, sales volumes, and resulting profits across tiers and formats is rarely addressed altogether. Prior research demonstrates how PLs and their multi-tier structure can contribute to retailers. Pauwels & Srinivasan (2004) found that the entry of PLs benefits retailers through higher unit margins but does not necessarily drive store traffic nor revenue growth. However, at the customer level, heavy PL users contribute less to total retailer profit than light PL users due to their tendency to purchase lower-priced items (Ailawadi & Harlam,2004). Moreover, budget[1] PLs tend to reduce retailer margins and cannibalize standard PLs, while increasing standard NB sales and overall category sales (Geyskens et al., 2010; Gielens, 2012). In contrast, standard and premium PLs are generally more effective at driving category growth than budget PLs.

Table 1: Selected literature on PLs performance in sales and profits

Paper	**Sales**	**Profits**	**PL Comparison**	**Format Comparison**
Paulwels & Srinivasan (2004)	Yes	Yes	PLs vs NBs	No
Ailawadi & Harlam (2004)	Yes	Yes	PLs vs NBs	No
Ailawadi, Paulwels & Steenkamp (2008)	Yes	No	PLs vs NBs	Service chain vs Value chain
Geyskens, Gielens & Gijsbrechts(2010)	Yes	No	Budget vs Standard vs Premium	No
Gielens (2012)	Yes	No	Budget vs Standard vs Premium	No
ter Braak, Dekimpe & Geyskens (2013)	No	Yes	Budget vs Standard vs Premium	No
Sethuraman & Gielens (2014)	Yes	No	PLs vs NBs	No
Keller, Dekimpe & Geyskens (2016)	Yes	No	PLs vs NBs	No
Hökelek, Lamey & Verboven (2017)	Yes	No	Budget vs Standard vs Premium	Traditional retailers vs Discounters
Widdecke, Keller & Gedenk (2023)	Yes	No	PLs vs NBs	Supermarkets vs Discounters
van der Plas, Dekimpe & Geyskens (2024)	No	Yes	PLs vs NBs	Conventional retailers vs Hard discounters
This Study	**Yes**	**Yes**	**Budget vs Standard vs Premium**	**Hypermarket vs Supermarket vs Convenience Store**

Different retail formats can moderate the role of PLs. Ailawadi, Pauwels & Steenkamp (2008) and Widdecke et al. (2022) found that found that service-oriented retailers tend to foster higher PL loyalty, whereas discounters benefit more from aggressive PL pricing strategies to attract price-sensitive consumers. Hökelekli, Lamey & Verboven (2017) found that standard PLs are the most effective in helping traditional retailers compete with discounters, while economy PLs tend to cannibalize other PL tiers. Van der Plas, Dekimpe & Geyskens (2024) demonstrated that

[1]Following the terminology used in Keller et al. (2022), this study refers to 'economy' private labels as 'budget' private labels.

consumers at hard discounters are highly responsive to price differences between national brands and private labels, both within the same store and across store formats.

While these studies offer valuable insights, existing research has primarily focused on the competition between private labels and national brands with limited finding regarding internal competition within retailers' multi-tier PL portfolios. Retailers increasingly invested in their multi-tier PLs not simply to counter national brands, but to strategically segment customers, optimize margins, and differentiate their store image (Nielsen, 2025). Understanding of how pricing affects each tier's performance, both individually and in relation to other tiers, can help retailers mitigate the risk of undermining profitability through unintended substitution effects or inefficient pricing structures. Unlike competition with national brands, intra-PL strategies are under the retailer's direct control, offering flexibility and potential for sustained competitive advantage.

Building upon these findings, our study contributes to the literature by examining the performance of PL tiers across different store formats within the same retail chain. Unlike prior research that primarily emphasizes PL–NB competition or focuses on aggregate format comparisons, we investigate how intra-PL pricing dynamics, both within and across tiers, influence sales and profitability at the format level. In response to the research opportunities highlighted by Keller et al. (2022), we explicitly investigate the sequential relationship between price changes, sales volumes, and resulting profits. This approach not only addresses the call for a more detailed investigation into the impact of multi-tier PLs across varied retail environments but also provides actionable implications for tailoring PL strategies by format to enhance total retailer performance.

2.2 Research Framework

Building on the identified theoretical and empirical research gaps, we propose the following research question. Given the differences in price effectiveness on sales among multi-tier PLs, do these differences persist across different store formats, and could this lead to varying levels of profitability across store formats? To do so, we follow our framework (Figure 1) that illustrates the relationships among profit, price, cost, and quantity of sales across multi-tier private labels.

The change in profit for each private label tier (budget, standard, premium) can be driven by changes in price, cost, and the corresponding changes in quantity sold. This relationship is captured as Δ Profit (π) where $\Delta\pi = f(\Delta Price, \Delta Cost, \Delta Sales)$[2]. Our framework proposes that the changes in quantity sales for each tier (Δ S: Budget, Δ S: Standard, Δ S: Premium) can be influenced by changes in price across all tiers (Δ P: Budget, Δ P: Standard, Δ P: Premium), suggesting an interdependent price dynamic among the tiers. In other words, we assume that the price of one tier can potentially affect the sales volumes of another, addressing interactions within a multi-tier pricing strategy documented by previous studies. By focusing on ΔS, we aim

[2]The full equation representing the change in profit can be approximated and expressed as: $\Delta\pi = S \cdot (\Delta P - \Delta C) + \Delta S \cdot (P_t - C_t)$

Δ Profit = f (Δ Price (P), Δ Cost (C), Δ Sales(S))				Δ P Budget	Δ P Standard	Δ P Premium
Δ π	Δ C	Δ P	Δ S	Δ S = f(P)		
Δ π : Budget	Δ C : Budget	Δ P : Budget	Δ S : Budget	Budget Brand Price Elasticity	Cross Price Elasticity	Cross Price Elasticity
Δ π : Standard	Δ C : Standard	Δ P : Standard	Δ S : Standard	Cross Price Elasticity	Standard Brand Price Elasticity	Cross Price Elasticity
Δ π : Premium	Δ C : Premium	Δ P : Premium	Δ S : Premium	Cross Price Elasticity	Cross Price Elasticity	Premium Brand Price Elasticity

Brand Price Elasticity
PL-tiers Cross Price Elasticity (Downward Substitution)
PL-tiers Cross Price Elasticity (Upward Substitution)

Figure 1: Multi-Tier Private Label Profitability: (Cross) Price Elasticity and Substitution Effects Framework

to directly capture the responsiveness of sales volumes of each private label tier to price changes.

We utilize this framework to establish an empirical model that quantifies the impact of price changes on profits across different store formats. This model will incorporate the inter-tier price effects to more accurately predict profitability shifts in response to pricing strategies.

Despite proposing a structural relationship between price, sales, and profit across PL tiers, our framework does not hypothesize specific expected relationships between cross-tier price changes and sales. The complexity of market dynamics and consumer behavior allows for a range of possibilities, including upward substitution, where changes in the prices of Budget or Standard tiers might influence the demand for higher-tier brands, and downward substitution, where changes in the prices of Standard or Premium tiers could affect demand for lower-tier brands (Figure 1). The relationship of price changes across tiers (i.e., upward substitution and downward substitution) may result in positive, negative, or null effects on sales volumes. The null effects occur when each tier has significant different positioning with different customer segments (Martos-Partal et al., 2013).

Moreover, our framework does not impose specific budget constraints within categories, allowing us to propose a broader range of consumer responses to price changes without restricting the scope of potential impacts. The absence of predefined budget constraints acknowledges that consumer purchasing decisions are not solely driven by category-specific budgets but are also influenced by perceived value, brand loyalty, and available alternatives across the entire store offering.

If PL tiers can be substitutable by one another, the relationship of price changes across tiers will be positive meaning that an increase in one tier price could lead to an increase in another tier price by making another tier become relatively cheaper. For example, if the price of the Premium tier increases, consumers may find the Standard or Budget tiers more appealing, not just because of a lower price, but also due to the diminished perceived value gap between the tiers. When faced with a set of alternatives, a relative price increase in one option can significantly enhance the attractiveness of the others, provided the goods are considered close substitutes (e.g., Lichtenstein

& Bearden, 1989). Conversely, if the price of the Budget tier were to increase, this could narrow the perceived price gap between the Budget and higher tiers such as Standard and Premium. Under these circumstances, consumers might reassess their value-for-money proposition. For instance, a smaller price differential might make the Standard and Premium tiers appear more attractive, offering perceived better quality or features for a slight increase in cost (e.g., Rao & Monroe, 1989). This could encourage consumers to "trade up" within the same brand's product line, especially if the quality differential is perceived to justify the relatively small additional expense.

The relationship of price changes across tiers can also be negative. This means that an increase in the price of one tier might lead to a decrease in the sales of another. For example, if the price of the Premium tier increases significantly, it might lead to a decrease in the sales of the Standard and Budget tiers. This can occur because the higher price point of the Premium tier may elevate the overall brand perception to a premium level, causing the brand to be perceived as less accessible or too expensive for budget-conscious consumers. This can alienate a portion of the brand's customer base who previously might have considered products from the Standard or Budget tiers but now feel that the brand on the whole has moved beyond their typical spending range (e.g., John et al., 1998; Kahneman et al., 1986). An increase in the Premium tier's price might also set new price expectations for the brand, making the Standard and Budget products seem less appealing to consumers who do not perceive enough quality or value difference to justify the cost, even at lower price points (e.g., Lichtenstein et al., 1993; Ailawadi et al., 2001). As a result, customers might opt for competing brands where they perceive better value across the price spectrum, resulting in an overall decline in sales across the Standard and Budget tiers. On the other hand, an increase in the price of the Budget tier could also negatively impact the sales of the Standard and Premium tiers. This scenario can occur through a process known as the negative halo effect, where the increased price of the Budget products may lead consumers to perceive the entire brand as less affordable or less value-driven, thus deterring these consumers from engaging with the brand altogether, rather than encouraging them to trade up to higher-priced tiers (e.g., Zeithaml, 1988). This could result in a significant segment of the customer base leaving for more competitively priced alternatives, thereby reducing the overall traffic and potential sales across all tiers. The price increase at the Budget level might also reset consumer expectations regarding the brand's pricing strategy, making even the Standard and Premium tiers seem less attractive if consumers believe that the brand is generally moving towards higher price points (e.g., Hamilton & Chernev, 2013). This shift in perception could lead to decreased sales in the higher tiers as consumers reevaluate their willingness to pay within the context of the new pricing structure, potentially seeking better-perceived value elsewhere.

In summary, this research leverages the outlined framework to construct an empirical model that systematically investigates the interconnected relationships between price, sales, and profit across different private label tiers within the same retail chain. Drawing on established findings from previous literature and theories in consumer behavior, we formulate the initial structure of our model to reflect these scholarly insights. This approach ensures that our model is theoretically sound. By intentionally not imposing any initial hypotheses on the relationships of cross-price elasticities, we maintain the flexibility to empirically uncover whether the influences are positive, negative, or null. This allows us to adapt our expectations based on observed data, accommodating a range of outcomes that reflect the variety of consumer responses to price changes.

3 Data and Measures

3.1 Empirical Setting

To investigate whether the differences in price effectiveness among multi-tier PLs persist across various store formats and how this influences profitability levels within those formats, we utilize detailed scanner data available from January 1, 2014, to November 30, 2016 obtained from a Nordic grocery retailer. The retailer operates under three specific store formats including hypermarkets, supermarkets, and convenience stores. Each format is designed to meet the varied shopping needs and preferences of different customer segments across regions. Moreover, the retailer owns the private labels which are accounted for more than 20 % of sales across these regions.

The retailer operates several private labels, which we have categorized into three tiers based on their distinct customer appeal and product description. These tiers follow the retailer's internal classification, which reflects consistent positioning in terms of price, quality, and target segment across store formats. The budget tier offers everyday items at competitive prices through large-scale purchasing and simple packaging, tailored to meet the needs of consumers who prioritize price over premium features. The standard tier offers a diverse product range, from basic staples sourced from local manufacturers to international producers, all noted for their consistent quality and often associated with sustainable benefits. The premium tier features ecologically produced goods and is marketed as high-quality products with a focus on distinctive taste, and regional authenticity. These premium products are typically promoted as suitable for special occasions or customers seeking an elevated shopping experience, reflecting how the retailer differentiates them from lower-tier alternatives.

In contrast, national brands are not organized into clearly defined tiers within the data. While price differences exist across national brands, these do not map cleanly into consistent tier categories due to variation in brand positioning and product attributes across categories. For this reason, we do not impose a tier structure on national brands based solely on price levels.

3.2 Data

3.2.1 Selected Stores and Relevant Products

The dataset is obtained from the retailer's loyalty membership database. The data includes detailed purchase information from selected customers, whose initial purchase is from the hypermarket. Their purchase information and shopping behavior information were then tracked across all store formats within the same retailer chain. Since these customers can make purchases at any store within the same retail chain, we minimize potential geographic and economic disparities by zooming in on three specific stores, representing one of the formats (hypermarket, supermarket, and convenience store) and located within the same city and most frequently visited by these customers.

Although our dataset provides detailed customer purchase information across store formats, it limits information to only the brands and categories available in our loyalty data. To overcome this, we focus on analyzing multitier PLs that are consistently purchased across the selected hypermarket, supermarket and convenience store. To ensure comparability across formats, we further restrict the analysis to a consistent set of products observed in multiple store formats, thereby minimizing differences driven by the product mix. This allows us to more accurately assess pricing strategies and brand performance across these formats.

First, we select PL products that are purchased at least once every two weeks, ensuring sufficient variability in price and performance observations over the data collection period. This threshold helps us avoid analyzing products with sporadic or seasonal sales patterns that could skew elasticity or profitability estimates. Next, we include only those national brand products that share similar descriptions with our selected PLs, guaranteeing that our comparisons are made between equivalent items. Finally, because our aim is to compare both within-brand tiers and across store formats, we limit our scope to product categories that have at least two multi-tier PLs offered in at least two different store formats. This restrictive selection helps maintain the validity of our comparisons across tiers and formats.

To illustrate this selection process, consider the category of biscuits. Although biscuits are available across different PL tiers and several national brands, not all product variants are suitable for comparison. Some biscuit types, such as gingerbread, are highly seasonal and typically purchased only during specific holidays like Christmas. These items do not meet our biweekly purchase threshold and could distort estimates of price elasticity and profitability. Others, such as whole grain or specialty biscuits, may be exclusive to premium PLs or high-end national brands, making them unavailable in lower-tier PLs or mass-market brands. Including such products would compromise comparability across both tiers and store formats. Therefore, in line with our selection criteria, we focus on commonly available product descriptions, such as plain digestive biscuits, that are consistently offered under all PL tiers and by major national brands, and are present in at least two different store formats. This ensures that the products we analyze serve similar consumer needs and enables us to isolate the effects of tier and format without confounding variation from product differentiation or seasonal demand.

After selecting, we retain five categories including biscuit, canned vegetable, cereals, pasta and raw nuts and dried fruits (Table 2). The availability of these products across different store formats varies. While the hypermarket and supermarket generally offer a wider range of products across all three brand tiers (basic, standard, premium), the convenience store has a more limited selection, typically featuring only basic and standard tiers, with only one category available. This difference likely stems from the space constraints and targeted assortment strategies characteristic across physical store formats. It is worth noting that our empirical setting competition between the basic and standard tiers, with no evident instances of competition between standard and premium tiers.

Table 2: Selected Multitier (B: Budget, S: Standard P: Premium) PLs Products and Their Availability Across Different Formats

Category	**Format**	**Example of product description**	**B**	**S**	**P**
Biscuit	Hypermarket	digestive	x	x	
	Supermarket		x	x	
Canned Vegetables	Hypermarket	tomato, corn, champignon, olive	x	x	x
	Supermarket		x	x	x
	Convenience		x	x	
Cereals	Hypermarket	cornflake, muesli, raisin	x	x	x
	Supermarket		x	x	
Pasta	Hypermarket	spaghetti, penne, gnocci	x	x	x
	Supermarket		x	x	x
Raw nuts, dried fruits	Hypermarket	plum, raisin, apricot	x	x	x
	Supermarket		x	x	x

Despite the wide assortment of products offered by the retailer, our final selection is limited to five product categories. This limited number of categories results from both data constraints and the stringent criteria necessary for valid cross-format comparisons. First, only a subset of categories features products available across PL tiers (budget, standard, premium) and across at least two store formats. Many categories either lack a full PL tier structure or are not consistently present across store formats particularly in the convenience store. Second, to support reliable estimation, we retain only products that meet our earlier biweekly purchase threshold.

Consequently, only one category, which is canned vegetables, meets these criteria across all three store formats, including the convenience store. While this limited representation might appear restrictive, it remains analytically meaningful. First, we define our research scope and selection criteria ex-ante, independent of final product availability, to maintain transparency and avoid selection bias. Second, the inclusion of the convenience store, even with just one qualifying category, provides a valuable contrast. It allows us to explore how multi-tier PLs perform in the most space-constrained and operationally distinct retail format. Rather than generalizing across all categories, our findings from the convenience store offer format-specific insights, highlighting the dynamics and limitations of PL tier strategies in constrained environments where assortment depth is minimal.

We summarize our final data on customer spending across selected product categories by store format in Table 3. The summary of customers spending across Multitier PLs implies varied multitier PLs performances across formats. The hypermarket, the largest format, has the most visitors (4,482) but shows moderate market share for budget (11%) and premium (10%) PL tiers, with relatively large share on standard tier products (38%). The supermarket, though smaller, has higher market share in the premium tier (15%) compared to the hypermarket. It is important to note that in our study, the convenience store is analyzed with only the canned vegetable category, yet it shows higher market shares for both the budget (36%) and standard (48%) tiers. Despite the varying popularity between the budget and premium tiers across five categories, the standard tier appears as the most established and dominant PL tier in our setting.

Table 3: Customers and their spending on selected product categories by store format

	Hypermarket	**Supermarket**	**Convenience**
Size (m^2)	4,252	2,155	497
Total unique brands available	39	40	13
Total unique products available	306	282	62
Total visitors	4,428	2,927	915
Avg Market Share for Budget	11	7	36
Avg Market Share for Standard	38	28	48
Avg Market Share for Premium	10	15	-

Notes: Reported across 135,776 shopping trips of five selected product categories (though, one for the convenience store) from 4,921 customers from the same demographic area visiting these store formats. The table reported the size (square meters), the number of brands and products observed, and the average market share for each PL tier in each format per visit (%).

3.3 Variable Operationalization

Table 4 provides details about the operationalization of the variables in our study. We focus primarily on two dependent variables: sales and profits. The main independent variable in the empirical analysis is the price of PLs, which is constructed as a sales-weighted average across its SKUs (Datta et al., 2022).

In addition to PL prices, we include several control variables to account for broader market conditions and demand fluctuations. The national brand price is operationalized as the market share–weighted average price of all other brands within the same category, excluding the focal private label tiers (budget, standard, and premium), and serves as a control for the competitive pricing environment. We further control for promotional intensity using feature and display activity, as well as seasonal effects through holiday indicators.

All variables are aggregated biweekly (referred to as *week t* throughout the analysis) to ensure continuity in our data and to prevent loss of information from excessive granularity. This aggregation allows for appropriate temporal adjustments that can capture lagged effects between price adjustments and brand performance. The final panel consists of 76 biweekly periods for each category–tier–format combination.

Table 4: Variable Operationalization

Variable	Description and Operationalization
$S_{ijk,t}$	Total Unit sales for PL Tier i in category j in store format k in week t.
$\text{Profits}_{ijk,t}$	Total Profits for PL Tier i in category j in store format k in week t.
$\text{Price}_{ijk,t}$	Price of PL Tier i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in local currency per unit (i.e., 100 gram).
$\text{NBPrice}_{jk,t}$	Average price of national brands in category j in store format k in week t, computed as a sales-weighted average across their SKUs sold in period t, expressed in local currency.
$\text{cost}_{ijk,t}$	Costs of PL Tier i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in local currency.
$\text{FD}_{ijk,t}$	Intensity of feature and/or display support for PL Tier i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in number range from 0 to 1.
Holiday_t	An indication variable equal to 1 it is a national holiday in week t.

3.4 Descriptives

Table 5 and 6 present descriptive statistics for multitier PLs prices and performances across different store formats within our dataset. We observe that the standard tier consistently dominates in terms of sales across all categories and store formats. However, the performance between budget and premium tiers varies; for instance, in the hypermarket within the cereals category, sales for budget and premium tiers are nearly equal, whereas in the pasta category, such gaps are less evident in the supermarket. Despite these variations in sales, total profits across tiers generally align with tier positioning, with higher tiers typically yielding higher profits (Keller et al., 2022).

Regarding PLs pricing, the budget tier consistently offers the lowest prices, but the gap between the standard and premium tiers is not uniform across categories. For example, in the category of canned vegetables, the price of standard tier products is closer to those of the premium tier, indicating a smaller price differentiation. In contrast, in the pasta category, the price gap places the standard tier closer to the budget tier, suggesting a broader pricing strategy that varies significantly by category.

In addition to cross-sectional differences, prices seem to vary over time within each store format, providing the empirical variation used in our analysis. Price adjustments occur regularly across categories, although they are not always implemented simultaneously across store formats, reflecting format-specific pricing decisions. It also shows that prices for the same PL tiers are not identical across formats, indicating that retailers already apply some degree of format-specific pricing. These differences are evident across several categories, where identical tiers are priced at different levels in the hypermarket, the supermarket, and the convenience store.

Importantly, these observed price differences are not driven by aggregation or assortment composition effects, as our analysis is conducted at the product level using consistent brand–product definitions across formats. This ensures that the estimated price effects reflect actual price variation rather than differences in the assortment mix.

4 Method

In the research framework, we propose that the change in profit for each private label tier can be influenced by changes in prices and corresponding changes in quantity sold for that tier while the changes in sales for each tier can be affected by changes in prices across all tiers. This structure addresses an interdependent price dynamic among the tiers and potential cannibalization effects within PLs. To assess how price adjustments consequently impact overall store profitability, taking into account the distinct contributions of each PL tier, we first estimate sales-response models for each tier (in each category and store format) and calculate estimated changes in sales for given changes in prices of other PL tiers. We then estimate profits-response models for each tier (in each category and store format) to obtain the effect of prices on profits. Table 7 summarizes the steps implemented in this study with their purposes and corresponding approach and relevant variables and parameters.

4.1 Sales-Response Model Specification

In order to quantify the effect of price changes on sales across different PL tiers, we adopt an error correction (EC) specification. This specification allows us to estimate the short-run elasticity of prices while accounting for potential long-run equilibrium relationships (Pauwels et al., 2007). In our sales response model specification, we use linear model to avoid the aggregation bias that might happen in another transformed specification such as log-log specification (Datta et al., 2022). Moreover, the linear model allows us to directly calculate estimated changes in sales without the need for further transformation.

Adopting an error-correction specification, the model for PL tier i sales in category j in store

Table 5: Descriptive statistics of multitier PLs performances across store formats

	Hypermarket	Supermarket	Convenience
Biscuit (unit: 100 gram)			
Budget PL Sales	53.47 (25.99)	31.89 (16.96)	-
Budget PL Profits	20.53 (12.55)	11.92 (7.39)	-
Standard PL Sales	429.32 (149.91)	71.11 (45.18)	-
Standard PL Profits	485.34 (133.13)	107.57 (47.55)	-
Canned Vegetables (unit: 100 gram)			
Budget PL Sales	1,333.95 (261.57)	351.99 (75.12)	142.90 (63.00)
Budget PL Profits	388.56 (103.71)	92.21 (26.54)	69.33 (22.77)
Standard PL Sales	3,502.93 (632.59)	836.66 (288.46)	134.57 (71.93)
Standard PL Profits	2,864.85 (416.07)	791.85 (147.00)	141.71 (43.29)
Premium PL Sales	382.84 (212.31)	166.16 (69.67)	-
Premium PL Profits	279.38 (92.01)	146.64 (63.13)	-
Cereals (unit: 100 gram)			
Budget PL Sales	168.22 (38.37)	33.22 (15.09)	-
Budget PL Profits	10.01 (7.06)	1.50 (2.85)	-
Standard PL Sales	565.24 (111.87)	203.64 (46.81)	-
Standard PL Profits	226.53 (63.49)	105.73 (26.80)	-
Premium PL Sales	119.54 (87.44)	-	-
Premium PL Profits	67.02 (34.61)	-	-
Pasta (unit: 100 gram)			
Budget PL Sales	522.37 (103.74)	64.34 (27.06)	-
Budget PL Profits	120.58 (27.86)	11.27 (4.99)	-
Standard PL Sales	383.95 (100.43)	116.64 (45.76)	-
Standard PL Profits	97.59 (44.96)	34.32 (13.50)	-
Premium PL Sales	76.12 (42.78)	33.16 (16.24)	-
Premium PL Profits	44.52 (24.48)	16.14 (8.94)	-
Raw nuts and dried fruits (unit: 100 gram)			
Budget PL Sales	65.43 (21.74)	17.76 (9.70)	-
Budget PL Profits	59.92 (34.98)	15.38 (10.61)	-
Standard PL Sales	123.24 (39.53)	59.87 (30.06)	-
Standard PL Profits	301.73 (117.76)	147.75 (91.09)	-
Premium PL Sales	50.28 (15.02)	33.26 (11.11)	-
Premium PL Profits	143.53 (41.64)	94.71 (32.14)	-

Notes: Reported across 233,456 shopping trips from 5,384 customers from the same demographic area visiting these store formats. The table presents the mean unit sales (SD) and mean profits (SD) for each PL tier across five categories. The unit of profits is in the local currency.

Table 6: Descriptive statistics of multitier PLs and national brand (NB) pricing across store formats

	Hypermarket	**Supermarket**	**Convenience**
Biscuit (unit: 100 gram)			
Budget PL Price	1.71 (0.13)	1.73 (0.22)	-
Standard PL Price	2.97 (0.34)	3.54 (0.46)	-
NB Price	3.92 (0.43)	4.26 (0.41)	-
Canned Vegetables (unit: 100 gram)			
Budget PL Price	1.71 (0.08)	1.65 (0.11)	1.93 (0.22)
Standard PL Price	2.61 (0.20)	2.70 (0.34)	2.91 (0.56)
Premium PL Price	2.71 (0.43)	2.79 (0.32)	-
NB Price	3.47 (0.26)	3.69 (0.35)	4.36 (1.44)
Cereals (unit: 100 gram)			
Budget PL Price	1.65 (0.08)	1.75 (0.19)	-
Standard PL Price	2.92 (0.15)	3.03 (0.11)	-
Premium PL Price	2.51 (0.25)	-	-
NB Price	3.99 (0.42)	4.37 (0.51)	-
Pasta (unit: 100 gram)			
Budget PL Price	1.22 (0.10)	1.04 (0.12)	-
Standard PL Price	1.47 (0.18)	1.54 (0.25)	-
Premium PL Price	2.46 (0.48)	2.08 (0.52)	-
NB Price	1.48 (0.12)	1.61 (0.12)	-
Raw nuts and dried fruits (unit: 100 gram)			
Budget PL Price	6.75 (0.69)	6.80 (0.65)	-
Standard PL Price	7.67 (0.59)	7.75 (1.18)	-
Premium PL Price	11.51 (1.17)	11.96 (1.59)	-
NB Price	8.20 (1.68)	7.80 (1.76)	-

Notes: Reported across 233,456 shopping trips from 5,384 customers from the same demographic area visiting these store formats. The table presents the mean price per unit (SD) across five categories. The unit of price is in the local currency.

Table 7: Estimation Steps and Methods

Purpose	**Approach**	**Relevant Variables/ Parameter**
Step 1: Estimating Sales-Response Model given interdependent price dynamic among the tiers	Employing Error Correction Model	Change in (quantity) sales as a dependent variable and changes in prices across multi-tier PLs as independent variables
Step 2.1: Calculating elasticities	Normalizing estimated parameters	Price coefficients ($\hat{\alpha}_{1ijk}$, $\hat{\beta}_{(i,l)jk}$) from estimated model in Step 1
Step 2.2: Calculated expected changes in sales given interdependent price dynamics among the tiers	Fitting changes in sales in the estimated model from step 1	Estimated changes in sales for given changes in own prices and changes of other PL tiers prices at t ($\Delta\hat{S}_{ijk,t}$)
Step 3: Estimating Profits-Response Model	Employing Error Correction Model	Change in profits as a dependent variable and changes in estimated sales ($\Delta\hat{S}_{ijk,t}$) from given changes in price across multi-tier PLs at t and its own price change as independent variables
Step 4: Calculating responsiveness of profit to a change in price	Normalizing estimated parameter	Price coefficients ($\hat{\tau}_{1ijk}$) from estimated model in Step 3

format k is:

$$\begin{aligned}(1)\quad \Delta S_{ijk,t} &= \alpha_0 + \alpha_{1ijk}\Delta Price_{ijk,t} + \sum_{l=1}^{L-1}\beta_{(i,l)jk}\Delta Price_{ljk,t}\\ &+ \beta_{2jk}\Delta NBPrice_{jk,t} + \beta_{3ijk}FD_{ijk,t}\\ &+ \gamma_{ijk}[S_{ijk,t-1} - \theta_0 - \theta_{1ijk}Price_{ijk,t-1} - \sum_{l=1}^{L-1}\vartheta_{(i,l)jk}Price_{ljk,t-1}]\\ &+ \beta_{4ijk}Holiday_t + \beta_{5ijk}Week_t + \beta_{6ijk}Year_t\\ &+ \beta_{7ijk}CopulaPrice_{ijk,t} + \beta_{7ijk}CopulaNBPrice_{jk,t} + \varepsilon_{ijk}\end{aligned}$$

where $\Delta X_t = X_t - X_{t-1}$ and subscript $(i,l)jk$ denotes competing PL tier of PL tier i within category j in store format k. The sum over l runs from 1 to $L-1$, where L depends on the number of PL tiers available in each category and format. In practice, L could be 2 or 3, as not all categories and store formats offer all three tiers of PLs. In addition to variables of interest, we added the Gaussian copula for $Price_{ijk,t}$ and $NBPrice_{jk,t}$ to address the potential presence of endogeneity (e.g., idiosyncratic changes in consumer preferences for brands) (Datta et al., 2022).

In the specified error-correction model, the coefficient γ_{ijk} captures the speed and extent of adjustment back to the long-term equilibrium of PLs sales following a deviation (Pauwels et al., 2007). This coefficient multiplies the error correction term, which is the difference between the actual sales level of the previous period and its predicted equilibrium level based on their own prices and other competing PL tier prices. This coefficient helps quantify the internal feedback mechanism within the sales process, providing insights into the underlying stability and responsiveness of the market to pricing strategies across PL tiers over time. Moreover, to ensure valid inference given the time-series structure of the data, we correct the estimated standard errors for potential serial correlation and heteroskedasticity using the Newey–West (HAC) estimator (Newey & West, 1987). This correction is applied to all error-correction models used in the analysis.

In this error-correction model, we obtain short-term effects for its own price ($\hat{\alpha}_{1ijk}$) and cross PL tiers' prices ($\hat{\beta}_{(i,l)jk}$) on sales for each competing PL tier. Since different categories have different units of sales, we control for scale differences by converting the obtained parameters ($\hat{\alpha}_{1ijk}$, $\hat{\beta}_{(i,l)jk}$) to unit-free elasticities at mean. This is done by normalizing the estimated parameters with the ratio of the sample mean[3] of prices of each tier or competing tier(s) to sample mean of sales of each tier (Srinivasan et al., 2004; Datta et al., 2022). Thus we get,

$$\hat{\eta}_{1ijk} = \hat{\alpha}_{1ijk} * \frac{(\overline{Price}_{ijk})}{(\overline{Sales}_{ijk})}$$

$$\hat{\eta}_{(i,l)jk} = \hat{\beta}_{(i,l)jk} * \frac{(\overline{Price}_{ijk})}{(\overline{Sales}_{(i,l)jk})}$$

where $\hat{\eta}_{1ijk}$ is the estimated price elasticity for PL tier i and $\hat{\eta}_{(i,l)jk}$ is the estimated cross-price elasticities. We then compare these elasticities across categories and store formats.

Since we want to account for the changes in sales that are not isolated within tiers but are interdependent across the entire range of PLs due to cross-elasticity effects and potential cannibalization within the product line, we calculate estimated changes in sales for given changes in own prices and changes of other PL tiers prices at t, $\Delta\hat{S}_{ijk,t}$, using the estimated model (1). This estimated changes in sales ($\Delta\hat{S}_{ijk,t}$) is used in the subsequent profits-response model.

4.2 Profits-Response Model Specification

In order to quantify the effect of price changes on profits across different PL tiers, we adopt an error correction specification. This specification allows us to capture both short-term effects and long-term adjustments in profitability in response to changes in sales, prices and costs. This is necessary for understanding the immediate impacts as well as the more gradual adjustments that might occur in a grocery retail context. Moreover, it can handle scenarios where variables do not necessarily have to be cointegrated, offering flexibility in our modeling approach. Thus, we can estimate how changes in pricing affect total profits in the short run while also observing how these changes contribute to achieving a long-term equilibrium in profitability. The choice

[3]Since we observe irregular drops of regular prices in certain products, we use the sample median instead of mean to avoid the extreme values in time-series.

of implementing EC specification in the profits-response model also follows logically from its application in the sales-response model, maintaining consistency in our analysis.

Since the profits of PL tier i is influenced by its own pricing adjustments and corresponding changes in sales volumes as proposed, the model for PL tier i profits in category j in store format k is:

$$
\begin{aligned}
(2) \quad \Delta\pi_{ijk,t} &= \tau_0 + \tau_{1ijk}\Delta Price_{ijk,t} + +\tau_{2ijk}\Delta\hat{S}_{ijk,t} + \tau_{3jk}\Delta cost_{ijk,t} \\
&+ \kappa_{ijk}[\pi_{ijk,t-1} - \rho_0 - \rho_{1ijk}S_{ijk,t-1} - \rho_{2ijk}Price_{ijk,t-1} - \rho_{3ijk}cost_{ijk,t-1}] \\
&+ \tau_{4ijk}Holiday_t + \tau_{5ijk}Week_t + \tau_{6ijk}Year_t \\
&+ \tau_{7ijk}CopulaPrice_{ijk,t} + \upsilon_{ijk}
\end{aligned}
$$

where $\Delta X_t = X_t - X_{t-1}$ and $\Delta\hat{S}_{ijk,t}$ is obtained from the sales-response models.

In our profits-response model (2), we incorporate the term $\Delta\hat{S}_{ijk,t}$, which represents the estimated changes in sales for a particular PL tier, given the changes in prices of its own and other PL tiers. This variable is derived from the sales-response models and used to quantify how price adjustments in one tier influence the sales volumes and consequently the profits of another tier within the same category and store format. The inclusion of this estimated value allows our model to dynamically capture the ripple effects of price changes across PL tiers, acknowledging that pricing decisions in one tier can have significant spill-over effects on other tiers. We ensure that our profit analysis accounts for these interdependencies relationship and provides a more accurate estimation of profitability impacts, as it considers both direct and indirect effects of price changes. As in the sales-response estimation, we use Newey–West (HAC) standard errors to account for possible serial correlation and heteroskedasticity in the residuals of the profit-response models.

In the specified error-correction model, the coefficient κ_{ijk} captures the speed and extent of adjustment back to the long-term equilibrium of PLs profits following a deviation. It multiplies the error correction term, which is the difference between the actual profits level of the previous period and its predicted equilibrium level based on their own sales, prices and costs. This coefficient helps quantify the internal feedback mechanism within the profits generating process.

Controlling for dynamics of sales and prices across PL tiers, we are interested in short-term effects of changes in price on profits ($\hat{\tau}_{1ijk}$). Since different categories have different profit margin structure, we control for scale differences by converting the this estimated effect of price on profit ($\hat{\tau}_{1ijk}$) to unit-free elasticities at mean. This is done by normalizing the estimated parameter with the ratio of the sample mean of prices to sample mean of profit. Thus we get,

$$\hat{\Theta}_{1ijk} = \hat{\tau}_{1ijk} * \frac{(\overline{Price}_{ijk})}{(\overline{Profits}_{ijk})}$$

5 Results

5.1 Sales-Response Model

We report the results from Sales-Response model in table 8. Across all categories, own price elasticities are significant negative for the standard and premium tiers, indicating that price increases generally lead to reductions in sales volumes in for these PL tiers. Moreover, the premium tier tends to be more sensitive to price compared to the standard tier. The results for the budget tier are mixed, with some elasticities in particular formats showing positive price elasticity. This implies differing consumer perceptions for the budget PL, possibly influenced by perceived value. Cross-elasticities also exhibit mixed effects, suggesting both downward substitution and upward substitution.

In the biscuits category, the significant negative elasticity of the standard tier in both hypermarket and supermarket reflects a sensitivity to price increases, aligning with the general pattern observed across other categories. The budget tier, however, shows a significant positive elasticity in the hypermarket, suggesting that lower prices can drive up sales, potentially indicating a strong consumer preference for value in this category. There is no statistical evidence of substitution between tiers.

In the canned vegetables category, the significant negative elasticity of the standard tier are significantly negative across all three formats. Unlike the biscuits category, the budget tier shows a significant negative elasticity in the supermarket and convenience store suggesting price-conscious consumers for this category. There exhibits upward substitution in the budget tier for this category in the supermarket and convenience store. This mean that an increase in budget PL price in supermarket and convenience store leads to a slight increase in the standard PL sales.

In the cereals category, the premium tier exhibits very high negative elasticity in the hypermarket, suggesting that consumers are extremely price-sensitive and likely to switch to different alternatives when prices rise. Since there is no statistical evidence of substitution among PL tiers, none of the PL tier gains from this.

In the pasta category, the average elasticity is low compared to other categories suggesting the potential necessity of this category. Sales of budget PL do not seem to be significantly influenced by any PL tier price, including its own. However, there is a downward substitution in the supermarket. This mean that increase in premium PL in supermarket leads to an increase in the budget PL sales.

In the raw nuts, dried fruits, and granola bars category, sales of budget PL and premium PL are not significantly influenced by their own prices. There exhibit both upward substitution and downward substitution among PL tiers in both hypermarket and supermarket. For hypermarket, increase in budget PL price leads to an increase in premium PL sales while increase in premium PL price affect negatively to standard PL sales. An increase in standard PL price has a significant

Table 8: Estimated (cross) price elasticity ($\hat{\eta}$) on sales among multitier PLs (B: Budget, S: Standard P: Premium) by category across store formats from Sales-Response model and long-term adjustment coefficient ($\hat{\gamma}_{ijk}$) and adjusted R^2 of the model.

Category	Format	$\hat{\eta}$	Sales B	Sales S	Sales P	$\hat{\gamma}_{ijk}$	R^2
Biscuits	Hypermarket	Price B	2.37**	-0.26	NA	-0.70	0.4182
		Price S	0.87	-2.43**	NA	-0.91	0.6295
		Price P	NA	NA	NA	NA	NA
	Supermarket	Price B	-0.26	-0.39	NA	-0.94	0.5194
		Price S	0.65	-4.92***	NA	-0.97	0.7354
		Price P	NA	NA	NA	NA	NA
Canned Vegetables	Hypermarket	Price B	0.15	-0.20	-0.04	-1.0	0.5871
		Price S	-0.24	-2.06***	0.25	-1.0	0.8227
		Price P	-0.05	-0.06	-2.79***	-1.0	0.9428
	Supermarket	Price B	-1.30***	0.46*	0.22	-0.8	0.6212
		Price S	-0.24*	-2.56***	-0.35	-0.8	0.8819
		Price P	-0.21	-0.08*	-0.59	-0.8	0.5987
	Convenience	Price B	-2.32***	0.03***	NA	-0.9	0.7221
		Price S	-0.36	-2.09***	NA	-0.9	0.7703
		Price P	NA	NA	NA	NA	NA
Cereals	Hypermarket	Price B	-2.54***	-0.32	0.34	-1.09	0.6990
		Price S	0.49	-1.87**	-1.01	-1.00	0.5563
		Price P	-0.08	0.03***	-5.99***	-0.98	0.8144
	Supermarket	Price B	-1.36***	-0.13	NA	-1.09	0.5950
		Price S	0.18	-2.76***	NA	-0.83	0.5515
		Price P	NA	NA	NA	NA	NA
Pasta	Hypermarket	Price B	-0.40	0.22	0.55	-1.05	0.5576
		Price S	-0.02	-0.94***	0.41**	-1.03	0.6806
		Price P	0.04**	0.23	-1.81***	-0.85	0.7290
	Supermarket	Price B	0.25	0.33	-1.85	-0.90	0.5154
		Price S	0.14	-0.75***	-0.24	-1.08	0.6487
		Price P	0.25**	0.11	-0.86***	-0.92	0.5926
Raw Nuts, Dried Fruits & Granola Bars	Hypermarket	Price B	0.72	1.19	0.87*	-0.86	0.5397
		Price S	0.65**	-1.15***	-0.97	-0.79	0.4979
		Price P	-1.13	-0.69*	-0.47	-1.13	0.6507
	Supermarket	Price B	1.42*	1.03	-0.69	-0.86	0.5793
		Price S	-1.07*	-0.73	-0.25	-0.88	0.5921
		Price P	0.73*	-0.59	0.37	-1.00	0.6476

Note: *p<0.1; **p<0.05; ***p<0.01

positive effect on budget PL sales in the hypermarket but a negative effect in the supermarket.

The adjustment coefficients ($\hat{\gamma}_{ijk}$) from the Error Correction Model vary significantly across different categories, tiers and formats. The coefficients, being negative, indicate a consistent tendency for prices and sales to revert to equilibrium after deviations, but at different rates. For instance, categories with more negative coefficients, such as cereals, suggest a rapid response to price changes, which could be indicative of high consumer price sensitivity or a competitive market where deviations from typical pricing are quickly corrected. Conversely, categories with less negative coefficients, such as biscuits, might exhibit slower adjustments.

5.2 Profits-Response Model

We report the results from Profits-Response model in table 9. Across all categories, controlling for dynamics of sales and prices across PL tiers, effects of price on profits are significantly positive, as expected, though they vary considerably by category and store format. Given that these elasticities are normalized at the mean and unit-free, it is reasonable to observe higher elasticities for the budget tiers. This is attributed to their lower mean prices, which cause any effect on profit to appear disproportionately high relative to their mean value. Unlike results from the Sales-Response model, the correction coefficients in the Profits-Response model differ, indicating varying speeds at which profit adjustments occur towards equilibrium after price changes. This variation in correction coefficients, particularly the positive effects observed in the standard tier, implies that price adjustments in this tier can lead to a higher equilibrium state of profits.

In the biscuits category, the basic PL tier has higher price elasticity on profits in the hypermarket, suggesting that this tier is relatively more profitable in this format while the standard tier seems to generate more profits in the supermarket. The low adjustment coefficients, especially for basic PL in hypermarket, suggest a gradual return to profit equilibrium, potentially allowing for sustained periods of higher profitability following price adjustments.This combination of high profit elasticity and slow adjustment may be partly explained by our earlier finding from the Sales-Response model, where the basic tier in the hypermarket exhibited a positive relationship between price and sales. In this case, price increases not only boost margins but may also lead to increased demand. This uncommon but strategically valuable scenario helps sustain elevated profit levels over a longer period.

In the canned vegetables category, the supermarket tend to have higher profitability from price changes across PL tiers suggesting a potential prominent presence and perceived values of private labels in the supermarket. This might due to the price elasticity from Sales-Response model of the basic tier that is lower in the supermarket compared to the other tiers, together with significant cross-price elasticity in the supermarket. The convenience store shows relatively lower profit elasticities across tiers. This may be due to a combination of factors: lower reliance on private labels in the convenience format, higher operational costs, and slimmer profit margins. The

Table 9: Estimated price elasticity ($\hat{\Theta}$) on profits for multitier PLs (B: Budget, S: Standard P: Premium) by category across store formats from Profits-Response model and long-term adjustment coefficient ($\hat{\kappa}_{ijk}$) and adjusted R^2 of the model.

Category	**Format**	$\hat{\Theta}$	**Profits**	$\hat{\kappa}_{ijk}$	R^2
Biscuits	Hypermarket	Price B	6.83***	-0.07	0.53
		Price S	3.76***	-1.08	0.51
		Price P	NA	NA	NA
	Supermarket	Price B	5.93***	-0.64	0.51
		Price S	4.30***	-0.51	0.42
		Price P	NA	NA	NA
Canned Vegetables	Hypermarket	Price B	7.45***	-0.64	0.61
		Price S	3.87***	-1.23	0.68
		Price P	3.49***	-1.30	0.63
	Supermarket	Price B	9.10***	-1.14	0.70
		Price S	3.62***	-0.99	0.64
		Price P	4.29***	-1.68	0.65
	Convenience	Price B	5.00***	-1.11	0.62
		Price S	2.72***	-0.89	0.47
		Price P	NA	NA	NA
Cereals	Hypermarket	Price B	28.56***	-1.16	0.93
		Price S	7.65***	-0.57	0.66
		Price P	6.92***	-0.67	0.59
	Supermarket	Price B	39.65***	-1.17	0.88
		Price S	4.11**	0.15	0.46
		Price P	NA	NA	NA
Pasta	Hypermarket	Price B	6.10***	-1.19	0.71
		Price S	10.04***	-0.66	0.82
		Price P	3.86***	-0.63	0.70
	Supermarket	Price B	5.60***	-1.68	0.70
		Price S	7.25***	-1.21	0.75
		Price P	3.67***	-1.14	0.63
Raw Nuts, Dried Fruits & Granola Bars	Hypermarket	Price B	8.74***	-0.75	0.61
		Price S	4.51***	0.63	0.54
		Price P	4.98***	-1.04	0.67
	Supermarket	Price B	10.07***	-0.91	0.57
		Price S	4.86***	-0.54	0.58
		Price P	5.72***	-1.75	0.68

Note: *p<0.1; **p<0.05; ***p<0.01

adjustment coefficients are moderately negative across all tiers and formats, suggesting a steady but not immediate return to profit equilibrium following price changes. The premium tier exhibits a faster adjustment process. One possible reason is that the premium tier does not get affected from other tiers' prices changes, as shown in the Sales-Response model. This independence may lead consumers to respond more immediately to pricing changes, allowing the tier's profits to stabilize more quickly.

In the cereals category, the basic PL tier appears to be more profitable in the supermarket, while the standard tier shows stronger profit elasticity in the hypermarket. This pattern may be explained by the lower price elasticity of the basic tier in the supermarket and of the standard tier in the hypermarket, as shown in the Sales-Response model. When demand is less sensitive to price increases, retailers can raise prices without significantly reducing sales volume, making such adjustments more effective in increasing overall profits. The adjustment coefficients are generally moderately negative, suggesting that profit levels tend to revert steadily to equilibrium following a price change. However, an exception is observed in the standard tier in the supermarket, which shows a positive adjustment coefficient. This implies that deviations from the profit equilibrium, such as a temporary increase in profits due to a price change, do not necessarily return to a long-term equilibrium. One possible interpretation is that consumers in the supermarket setting may gradually adapt to the new price as a norm, especially for mid-tier products like standard PLs that are positioned as reliable and consistent. This slow or reinforcing response may reflect changes in consumer expectations or perception of value, where the new price point becomes accepted as the standard over time, preventing a reversion to previous profit levels.

In the pasta category, the hypermarket tends to have higher profitability from price changes across PL tiers suggesting a stronger consumer loyalty toward PLs. This is supported by descriptive statistics (Table 6) showing that the average prices of pasta across all PL tiers are higher in the hypermarket than in the supermarket, potentially signaling higher perceived quality or broader product selection in this format. Despite the slightly higher price elasticity across tiers in the hypermarket from the Sales-Response model, the magnitude of profit elasticities suggests that price increases still effectively drive profitability. This indicates that while consumers do react to price changes, the combination of volume, higher margins, and perceived value more than compensates, resulting in overall profit growth. In terms of adjustment, the hypermarket shows a generally slower return to profit equilibrium compared to the supermarket. This slower adjustment may be attributed to more stable or habitual purchasing behavior in the hypermarket. Such patterns may delay immediate responses to price changes, allowing elevated profit levels to persist over longer periods.

In the raw nuts, dried fruits, and granola bars category, the basic tier appears to be more profitable in the hypermarket, while the standard tier and premium tier show stronger elasticity in the supermarket. This finding may be partly explained by the findings from the Sales-Response model: in the hypermarket, the basic tier was less affected by its own price changes, suggesting that modest price increases can improve margins without significantly reducing sales. In contrast, both the standard and the premium tiers in the supermarket showed weaker responses to their own price and minimal cross-price effects, indicating that these products can maintain steady sales even when priced higher, resulting in improved profitability. In terms of adjustment, the premium tier shows a relatively faster return to profit equilibrium in both hypermarket and supermarket. On the other hand, we observe a positive adjustment coefficient for the standard tier in the hypermarket. This suggests that deviations from the standard tier's profit equilibrium may persist or even escalate over time, possibly due to shifting perceptions of value or changes in competitive dynamics within this mid-range offering.

6 Discussion

6.1 How Multitier PLs Perform Across Store Formats?

This study explores how price effectiveness on sales varies across multi-tier private labels (PLs) and store formats, and whether these differences translate into divergent profitability outcomes. Specifically, we examine whether PL tiers, which are budget, standard, and premium, respond differently to pricing strategies depending on the store format (hypermarket, supermarket, or convenience store) within the same retail chain. Using a stepwise empirical framework that links price changes to sales and then to profits, we estimate both immediate and sequential effects of pricing across tiers and formats using Error Correction Models (ECM).

Our findings indicate significant variation in how PL tiers respond to price changes across formats. Across most categories and formats, standard and premium tiers consistently exhibit negative own-price elasticities, confirming that price increases tend to reduce sales volumes. This is consistent with prior research highlighting consumers' price sensitivity for higher-tier PLs (e.g., Gielens, 2012; Geyskens et al., 2010). However, the magnitude of these elasticities differs by format, suggesting that the same PL tier may exhibit stronger or weaker price responsiveness depending on the store format. This supports previous findings that store format plays a moderating role in influencing customer price responses, possibly due to differences in shopper missions, product assortment, or competitive benchmarks (Van der Plas et al., 2024).

In contrast, the budget tier shows greater heterogeneity, with occasional positive elasticities observed, particularly in the hypermarket. These findings align with prior work on price-quality signaling (Rao & Monroe, 1989), suggesting that some consumers may interpret price increases in lower-tier products as an indicator of improved value. These findings highlight the need for retailers to account for consumer perception dynamics when implementing pricing strategies for lower-margin tiers.

Our study shows that cross-tier substitution is limited across most formats and categories. Premium PLs show minimal responsiveness to price changes in lower tiers, implying that consumers view them as distinct rather than interchangeable. This is consistent with literature on niche differentiation and quality segmentation (Martos-Partal et al., 2013). This weak cross-tier substitution suggests that multi-tier PLs can often function as independent offerings rather than internal substitutes, giving retailers more flexibility to pursue differentiated pricing strategies without triggering extensive cannibalization.

While substitution across PL tiers is limited, the observed changes in sales indicate that demand adjustments are likely driven by sources beyond the PL portfolio itself. At the same time, the limited and mixed substitution patterns within PL tiers suggest that cross-tier responses depend on their relative positioning, particularly the price gap between adjacent tiers, where wider gaps may encourage downward substitution and narrower gaps may facilitate upward movement. Given the scope of our data, which is limited to selected stores within a single retail chain, we cannot directly identify whether these changes reflect switching from national brands, shifts across competing retailers, or changes in overall consumption levels. However, several plausible mechanisms may explain these patterns. First, private labels often compete more directly with national brands than with other PL tiers, suggesting that price changes may primarily shift demand between PLs and national brands rather than across PL tiers. Second, format-specific shopping missions may influence how demand responds; for example, in hypermarkets, price changes may affect basket size or category-level purchases, while in convenience stores, purchases are more mission-driven and less sensitive to price changes. Finally, the limited substitution across tiers may reflect relatively stable preferences within each tier, where consumers adjust quantities rather than switch between tiers in response to price changes.

These differentiated sales responses carry through to profitability. Results from the Profits-Response models indicate that pricing adjustments have a positive impact on profits across tiers, although the extent of this impact varies. Budget tiers, despite lower margins, tend to show stronger profit responsiveness, especially in hypermarket format since small price changes can yield relatively larger sales and margin gains. This aligns with recent work by Keller, Dekimpe, and Geyskens (2022), who emphasized the disproportionate profit impact from pricing actions in lower-tier PLs. Meanwhile, standard and premium tiers, although typically less elastic, still generate profitability gains, especially in store formats where consumers recognize their added value and are less likely to switch to lower-tier alternatives.

The comparative findings across formats suggest that PL performance is format-contingent. Hypermarkets benefit most from pricing actions on budget PLs, while supermarkets derive more profit gains from standard and premium PLs. In contrast, the convenience store, which is characterized by its limited assortment and simplified product mix, shows more muted responsiveness to pricing, likely due to fewer options available for substitution and a focus on immediacy and routine purchases rather than price-driven shopping.

Taken together, our findings suggest that while retailers already differentiate pricing across store formats, these strategies can be refined using evidence on tier-specific responsiveness and profitability. Rather than adjusting prices by rule of thumb or benchmarking across formats, retailers should base price decisions on the elasticity–profitability patterns identified for each tier. For example, in hypermarkets, where price sensitivity in budget tiers may be lower or even positive, retailers could explore selective price increases on budget PLs to improve margins without harming volume. In supermarkets, where standard and premium PLs show stronger price sensitivity but also yield higher profitability, moderate, carefully timed adjustments can help increase margins while maintaining quantity sold. In convenience stores, with limited assortment and higher price sensitivity, it may be most effective to maintain stable pricing on core products to retain baseline volumes and avoid deterring quick-stop shoppers. Overall, pricing refinement should rely on empirical monitoring of tier-specific elasticities rather than uniform or intuition-based markups.

Throughout this study, we present our results separately by category, tier, and store format to capture the heterogeneity in pricing responses across these dimensions. Given the limited number of product categories and the uneven availability of tiers across formats in our setting, aggregating these effects into a single summary measure would mask meaningful differences in how pricing operates across tiers and formats. This level of disaggregation also allows for clearer interpretation within each category, without conflating effects across different units of analysis, even though the discussion synthesizes the findings at a higher level.

While these findings highlight the role of pricing in shaping format-specific performance, price is only one element of the broader retail marketing mix (Blut et al., 2018; Gielens & Steenkamp, 2025). Retailers also differentiate store formats through assortment, promotions, and store characteristics, which can influence consumer behavior both independently and through their interactions with one another, including but not limited to pricing decisions. Our analysis isolates the price–sales–profit relationship to provide a clearer understanding of pricing effectiveness, but this should not be interpreted as suggesting that price is the dominant lever for format differentiation. Rather, pricing should be considered alongside other strategic elements that jointly influence consumer behavior across formats. Finally, our conclusions are derived from a retailer-focused perspective based on sales and profitability outcomes. While our framework captures consumer responses through observed purchasing behavior, it does not directly measure consumer perceptions such as price fairness or brand image.

6.2 Limitations

This study has several limitations, each of which presents opportunities for future research. First, our empirical results are inherently dependent on the nature and scope of our dataset, which primarily consists of grocery retailer data collected from consumers whose initial purchases were made at the hypermarket in a certain area. Consequently, our findings may not capture the full spectrum of shopping behaviors or preferences evident among the broader population. This limits the generalizability of our results to other customer segments and retail contexts. Future research could address this limitation by analyzing more diverse datasets, including consumers from multiple retail formats or less brand-loyal segments, to verify the robustness and general applicability of our conclusions.

Second, our results may be sensitive to the data selection criteria applied to ensure comparability across store formats and product tiers. In constructing the dataset, we restrict the sample to customers whose initial purchase occurred in the hypermarket, focus on a limited number of stores within a single city, and include only frequently purchased products and categories that are consistently available across formats. While these criteria help reduce noise from sparse observations and avoid confounding effects from differences in product availability, they may also limit the representativeness of the sample. As a result, the findings should be interpreted within the context of a controlled empirical setting rather than as fully generalizable across all customers, stores, and product categories. Future research could examine the robustness of these results by relaxing these selection criteria or using broader datasets that capture more diverse shopping patterns.

Third, due to data limitations, we did not incorporate additional marketing mix elements, such as advertising and promotional activities, which are known to substantially influence consumer decision-making processes. Omitting these variables does not invalidate our results, as the analysis isolates price–sales–profit dynamics within consistent store and category settings. However, it could potentially limit the completeness of interpretation, as unobserved promotional effects might amplify or attenuate measured price responses (Bijmolt et al., 2005). Future studies could thus enhance the comprehensiveness of results by integrating detailed data on marketing communications, promotional strategies, and in-store displays, enabling a deeper understanding of how these factors interact with pricing decisions to shape consumer behaviors and retail outcomes. Moreover, the use of retailer-level transactional data limits our ability to directly observe consumer perceptions, such as price fairness or brand image. As a result, our findings reflect the retailer side of pricing outcomes rather than both the retailer and consumer perspectives.

Fourth our analysis assumes interdependence among multi-tier PLs to estimate potential cross-price effects, yet the observed limited cross-tier elasticities in certain categories suggest that consumers may perceive these tiers as distinct and non-substitutable. This limitation implies that the assumed inter-tier relationships might not reflect actual consumer perceptions or behaviors across all product categories. Future research might employ consumer perception surveys or discrete-choice models to explicitly test and confirm the degree of substitution between PL tiers and refine the understanding of these relationships across different product categories and market segments (Gielens et al., 2021).

Fifth, while we explicitly model differentiation across private label tiers, we do not distinguish between tiers of national brands due to the absence of consistent tier classifications in the data. While price differences exist across national brands, these do not map cleanly into stable tier structures across categories. As a result, our analysis captures the overall competitive price environment rather than more granular brand-level positioning. Future research could explore more detailed competitive structures by incorporating richer brand-level information or external classification schemes.

Finally, our use of linear Error Correction Models (ECM) presupposes specific structural relationships between price, cost, sales, and their lagged effects, potentially restricting our analysis to linear dynamics. The reality of consumer behavior and pricing responses may involve more complex, nonlinear interactions not fully captured by our modeling approach. Future research could extend our findings by exploring alternative modeling frameworks, such as nonlinear or machine-learning-based approaches, that might capture more nuanced and dynamic relationships between prices, sales, and profitability.

References

Ailawadi, K. L., & Pauwels, K. (2008). Private-label use and store loyalty. *Journal of Marketing*. `https://journals.sagepub.com/doi/abs/10.1509/jmkg.72.6.019`

Ailawadi, K. L., & Harlam, B. (2004). An empirical analysis of the determinants of retail margins: The role of store-brand share. *Journal of Marketing*, *68*(1), 147–165.

Ailawadi, K. L., Neslin, S. A., & Gedenk, K. (2001). Pursuing the value-conscious consumer: Store brands versus national brand promotions. *Journal of Marketing*, *65*(1), 71–89.

Bijmolt, T. H. A., van Heerde, H. J., & Pieters, R. G. M. (2005). New empirical generalizations on the determinants of price elasticity. *Journal of Marketing Research*, *42*(2), 141–156.

Datta, H., van Heerde, H. J., Dekimpe, M. G., & Steenkamp, J.-B. E. M. (2022). Cross-national differences in market response: Line-length, price, and distribution elasticities in 14 Indo-Pacific Rim economies. *Journal of Marketing Research*, *59*(2), 251–270. `https://doi.org/10.1177/00222437211058102`

Gauri, D. K., Trivedi, M., & Grewal, D. (2008). Understanding the determinants of retail strategy: An empirical analysis. *Journal of Retailing*, *84*(3), 256–267.

Geyskens, I., Gielens, K., & Gijsbrechts, E. (2010). Proliferating private-label portfolios: How introducing economy and premium private labels influences brand choice. *Journal of Marketing Research*, *47*(5), 791–807.

Gielens, K. (2012). New products: The antidote to private label growth? *Journal of Marketing Research*, *49*(3), 408–423.

Hamilton, R., & Chernev, A. (2013). Low prices are just the beginning: Price image in retail management. *Journal of Marketing*, *77*(6), 1–20.

Hökelekli, G., Lamey, L., & Verboven, F. (2017). The battle of traditional retailers versus discounters: The role of PL tiers. *Journal of Retailing and Consumer Services*, *39*, 11–22.

John, D. R., Loken, B., & Joiner, C. (1998). The negative impact of extensions: Can flagship products be diluted? *Journal of Marketing*, *62*(1), 19–32.

Kahneman, D., Knetsch, J. L., & Thaler, R. (1986). Fairness as a constraint on profit seeking: Entitlements in the market. *American Economic Review*, *76*(4), 728–741.

Keller, K. O., Dekimpe, M. G., & Geyskens, I. (2016). Let your banner wave? Antecedents and performance implications of retailers' private-label branding strategies. *Journal of Marketing*, *80*(4), 1–19.

Keller, K. O., Dekimpe, M. G., & Geyskens, I. (2022). Adding budget and premium private labels to standard private labels: Established empirical generalizations, emerging empirical insights, and future research. *Journal of Retailing*, *98*(1), 5–23.

Keller, K. O., Geyskens, I., & Dekimpe, M. G. (2020). Opening the umbrella: The effects of rebranding multiple category-specific private-label brands to one umbrella brand. *Journal of Marketing Research*, *57*(4), 677–694.

Lichtenstein, D. R., & Bearden, W. O. (1989). Contextual influences on perceptions of merchant-supplied reference prices. *Journal of Consumer Research*, *16*(1), 55–63.

Lichtenstein, D. R., Ridgway, N. M., & Netemeyer, R. G. (1993). Price perceptions and consumer shopping behavior: A field study. *Journal of Marketing Research*, *30*(2), 234–245.

Martos-Partal, M., González-Benito, O., & Fustinoni-Venturini, M. (2015). Motivational profiling of store brand shoppers: Differences across quality tiers. *Marketing Letters*, *26*(2), 187–200.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708.

Pauwels, K., & Srinivasan, S. (2004). Who benefits from store brand entry? *Marketing Science*, *23*(3), 364–390.

Pauwels, K., Srinivasan, S., & Franses, P. H. (2007). When do price thresholds matter in retail categories? *Marketing Science*, *26*(1), 83–100.

Rao, A. R., & Monroe, K. B. (1989). The effect of price, brand name, and store name on buyers' perceptions of product quality: An integrative review. *Journal of Marketing Research*, *26*(3), 351–357.

Sethuraman, R., & Gielens, K. (2014). Determinants of store brand share. *Journal of Retailing*, *90*(2), 141–153.

Srinivasan, S., Pauwels, K., Hanssens, D. M., & Dekimpe, M. G. (2004). Do promotions benefit manufacturers, retailers, or both? *Management Science*, *50*(5), 617–629.

ter Braak, A., Dekimpe, M. G., & Geyskens, I. (2013). Retailer private-label margins: The role of supplier and quality-tier differentiation. *Journal of Marketing*, *77*(4), 86–103.

van der Plas, J., Dekimpe, M. G., & Geyskens, I. (2024). Mind the gap: National brands' sensitivity to price and line-length differentials at hard discounters versus conventional retailers. *Journal of Retailing*, *100*(2), 199–216.

Widdecke, K. A., Keller, W. I. Y., Gedenk, K., & Deleersnyder, B. (2022). Drivers of the synergy between price cuts and store flyer advertising at supermarkets and discounters. *International Journal of Research in Marketing*. `https://doi.org/10.1016/j.ijresmar.2022.10.001`

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22.

Article 2

Regular Prices vs. Discounts: How Pricing Strategies Perform Across Store Formats

Regular Prices vs. Discounts: How Pricing Strategies Perform Across Store Formats *

Tanetpong Choungprayoon † Rickard Sandberg ‡ Sara Rosengren §

Abstract

This study investigates how regular prices listed and discounts offered (i.e., temporary price reduction) influence brand sales across store formats within a single grocery retail chain. Using loyalty-based scanner data covering 55 brands across 14 categories from 2014–2016, we estimate error-correction models to quantify elasticities of regular prices and discounts in a hypermarket, a supermarket, and a convenience store. Regular price elasticities are negative across all store formats, with the strongest magnitude in the hypermarket and the weakest in the convenience store. Discount elasticities are positive and highest in the hypermarket, followed by the supermarket, indicating stronger promotional responsiveness in larger-format stores. The differential elasticities show that the impact of regular price increases generally exceeds that of discounts, suggesting asymmetry in customer responses. The second-stage results show that store formats significantly influence how brand and category factors determine pricing effectiveness. Results highlight that pricing effectiveness varies systematically by store format and that separating regular price and discount effects provides a better understanding of promotional pricing across retail environments.

Keywords: Discounts; Pricing; Grocery retailing; Store formats

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1 Introduction

Retailers in the grocery industry constantly face changing consumer preferences and shopping behaviors driven by dynamic micro and macroeconomic conditions (Scholdra et al., 2022). These conditions significantly affect households' shopping behavior, leading to adjustments in where and how much consumers shop and spend. In response to these shifts, many adopt multiformat retailing, where different store formats, such as hypermarket, supermarket, and convenience store, are designed to meet diverse needs, broaden reach, and enhance the shopping experience (Breugelmans et al., 2023; Dekimpe et al., 2023). Each store format facilitates distinct shopping goals, thus attracting customers with varied behaviors and preferences (gijsbrechts et al., 2018; Jindal et al., 2020).

Given these differences in consumer behavior across store formats, the effect of marketing mix instruments, particularly price and discount, are likely to vary (e.g. Shankar & Krishnamurthi, 1996; Haans & Gijsbrechts, 2011; Widdecke et al., 2022). While many studies have explored price and discount effects across brands, categories, or store formats (e.g., Pauwels et al., 2007, ;Haans & Gijsbrechts, 2011; Datta et al., 2022), few have considered all these factors systematically together. Examining price and discount effects simultaneously across brands, categories, and formats provides a more complete view of how these elements interact to influence brand performance, particularly for multiformat retailers who have to manage and navigate the complexities of multiple consumer environments.

Promotional pricing, a retail strategy involves either adjustments of the regular (baseline) price or the offering of temporary discounts, has been extensively studied, though the approaches to its analysis vary. Research typically integrates these adjustments into a 'final price' or treats them separately to address the distinct cognitive processing involved in evaluating regular prices and discounts (Kuntner & Teichert, 2016). Both regular price and discounts are important in consumer decision-making, but when analyzed together, distinct consumer responses to each may be overlooked. Neglecting the differences between them may also lead to biased estimates regarding price sensitivities (Lu et al., 2023). Thus, an analysis of how regular prices and discounts distinctly influence consumer behavior across different store formats can support effective promotional planning across various retail environments. For instance, a discount may drive sales for certain brands in supermarkets but have limited effect in convenience stores, reflecting the differential impact of pricing strategies across store formats. In practice, pricing decisions often involve selecting whether to prioritize regular prices or discounts, with choices determined by store format, product category, and brand factors.

The purpose of this study is to investigate the differentiated impacts of regular prices and discounts on brand performance across various categories and store formats within the same retail chain. By distinguishing and quantifying the effects of promoted discounts from the final retail price on brand sales, we contribute to addressing existing gaps in understanding the differential impacts of these components. Specifically, we examine the direct influences of store formats on pricing effectiveness. Pricing effectiveness may also depend on brand- and category-level characteristics, including discount frequency, discount depth, private label status, impulsiveness, storability, and competitive intensity. Therefore, we further analyze how store format moderates the relationships between these factors and pricing effectiveness. To achieve this, we utilize detailed scanner data from 2014 to 2016, obtained through the loyalty membership database of a Nordic grocery retailer operating as a system with individual store owners under the same retail-chain. In this system, promotional strategies are largely centralized, while individual stores have the flexibility to set their own prices.

In empirical analysis, we select 180 brands across 14 frequently purchased categories across store formats engaging in adjustments of the regular prices or the offering of temporary discounts. We follow a two-stage approach. In the first stage, we quantify the elasticities of regular prices and discounts on brand sales across categories and store formats. To mitigate potential bias stemming from differences in shopping intent across formats, we incorporate trip types as an additional control variable. This trip type is classified algorithmically from transactional basket data. Incorporating this construct helps ensure that observed differences in price responsiveness are not confounded by the underlying purpose of the shopping trip. In the second stage, we explore how store formats influence these elasticities as well as moderate how brand and category factors affect these pricing elasticities. Our findings suggest variations in how promotional strategies (i.e., changes in regular prices and changes in discounts) perform across different formats and how effects from brand and category factors are moderated. For example, the significant influence of store formats on the differential effects between regular price changes and discounts, particularly in convenience stores and supermarkets, indicates a unique consumer sensitivity to pricing strategies that is not uniformly mirrored across other store types. Additionally, the role of store formats in moderating brand and category factors, such as discount depth and breadth, especially in hypermarkets and supermarkets, shows that larger store formats can leverage scale and assortment diversity to make promotions more compelling and effective.

The findings of our study not only contribute to the understanding of how different store formats influence the effectiveness of promotional pricing strategies within a multi-format retail setting, but also offer actionable insights for retail managers. For example, the heightened responsiveness to discounts in hypermarkets and supermarkets can be used strategically to increase basket size and improve turnover, particularly for categories known for having wider discounts offered. The distinct effects observed in hypermarkets for private labels, where discounts sensitivity is higher, address the strategic importance of pricing these products correctly. The lack of significant effects from store formats on discount elasticity suggests a uniformity in how discounts are perceived across formats. This finding calls for a more tailored approach to discounting or decentralizing how the discount should be offered.

The rest of the paper is organized as follows. We provide a brief overview of relevant literature and our research framework in Section 2. We introduce the empirical setting, data and measure for this study in section 3 and present model-free evidence in section 4. We specify our two-stage approach to model in section 5. We present and discuss our results in Section 6 and 7 respectively.

2 Background and Research Framework

2.1 Literature Review

Previous studies have explored the effects of store formats, brand, and category factors on promotional pricing effectiveness. However, a comprehensive analysis that fully investigates the potential role of store formats in directly influencing promotional price effectiveness and moderating the impact of brand and category factors is limited. Table 1 provides an overview of the relevant literature on promotional pricing effectiveness, highlighting the key factors that influence this effectiveness and the various approaches to analyzing the differential effects of regular prices and discounts.

Not all research, however, has specifically focused on the role of physical store formats within the same retail chain in influencing the elasticities of promotional prices, nor have they extensively examined how brand and category factors can be affected differently across formats. Since promotional pricing typically involves either adjustments to the regular (baseline) price or the application of temporary discounts aimed at creating a perceived value for the consumer (van Heerde & Neslin, 2017), academic research has examined promotional pricing in different aspects—either by analyzing regular prices and discounts together (e.g., Pauwels et al., 2007; Datta et al., 2022) or by treating them as separate elements to capture their distinct effects on consumer behavior (e.g., Haans & Gijsbrechts, 2011; Widdecke et al., 2023). While existing studies have provided valuable insights into the effects of promotional pricing across various contexts, notable gaps remain, particularly in how these strategies are applied across multi-format retail settings.

A number of studies (e.g., Raju, 1992; Shankar & Krishnamurthi, 1996; Widdecke et al., 2023) have explored the differential effects of regular prices and discounts, highlighting the distinct ways these components influence consumer behavior. However, fewer studies examine their simultaneous impact on brand performance across categories and store formats, offering limited insights into how these effects interact in practical retail scenarios. Although previous research (e.g., Pauwels et al. (2007), Haans & Gijbrechts (2011), and Gauri et al. (2017)) has examined the moderating roles of brand and category factors on the effectiveness of price and discount strategies, the direct and moderating influences of physical store formats on these pricing elasticities remain underexplored. Moreover, these studies often involve different retail chains and rely on third-party data, which can amplify observed differences, leaving empirically uncertain how these dynamics manifest within a single retail chain using data sourced directly from the retailer itself.

Our study addresses these gaps in three ways. First, we explicitly distinguish between the effects of regular prices and temporary discounts on brand sales, allowing us to identify asymmetries

Table 1: Overview of literature within promotional price effectiveness: Influence of store format, brand and category factor

Author(s) and Year	**Store Format**	**Brand Factor**	**Category Factor**	**Differential Effects of Price and Discounts**	**Retail Setting**	**Data Source**
Raju (1992)	No	No	Yes	Yes	One Store	Retailer
Shankar & Krishnamurthi (1996)	Yes	Yes	No	Yes	Different Chains	Third Party
Dhar, Hoch, & Kumar (2001)	No	No	Yes	Yes	Different Chains	Third Party
Nijs, Dekimpe, Steenkamp & Hanssens (2001)	No	No	Yes	Yes	Different Chains	Third Party
Ailawadi, Harlam, César & Trounce (2006)	No	Yes	Yes	Yes	Within Chains	Retailer
Pauwels, Srinivasan & Franses (2007)	No	Yes	Yes	No	Within Chains	Retailer
Haans & Gijsbrechts (2011)	Yes	No	Yes	Yes	Within and Across Chains	Third Party
Gauri, Ratchford, Pancras & Talukdar (2017)	No	Yes	Yes	No	Within Chains	Retailer
Jindal, Zhu, Chintagunta, & Dhar (2020)	Yes	Yes	No	No	Different Chains	Third Party
Datta, van Heerde, Dekimpe & Steenkamp (2022)	No	Yes	Yes	No	Different Chains	Third Party
Widdecke, Keller & Gedenk (2022)	Yes	Yes	Yes	Yes	Different Chains	Third Party
This Study	**Yes**	**Yes**	**Yes**	**Yes**	**Within Chains**	**Retailer**

in how consumers respond to price increases versus promotional discounts across store formats. Second, we examine these effects within a multi-level framework, where store formats not only directly influence pricing effectiveness but also moderate the role of brand- and category-level characteristics. Third, we leverage detailed loyalty-card data from a single retail chain to analyze multiple store formats within a unified system, thereby reducing heterogeneity in pricing policies, competitive environments, and customer composition. Together, these contributions provide a more precise understanding of how pricing strategies perform across retail formats and how their effectiveness depends on the interaction between format, brand, and category characteristics, offering actionable insights for retailers while extending the understanding of pricing effectiveness in multi-format retail settings.

2.2 Research Framework

Building on the identified theoretical and empirical research gaps, we propose a framework (Figure 1) that guides our study to investigate the differentiated impacts of regular prices and discounts on brand performance across various categories and store formats within the same retail chain.

In this study, promotional price effectiveness refers to the responsiveness of brand sales to changes in pricing instruments, captured through the estimated elasticities of regular prices and discounts. We distinguish between two related but conceptually different outcomes. First, we examine the effectiveness of discounts, measured as the sensitivity of sales to changes in temporary price reductions. Second, we analyze the differential effect between regular prices and discounts, which captures the relative magnitude of their impact on sales, rather than differences in sales levels. This distinction is important, as our focus is not on absolute sales differences, but on how strongly consumers respond to regular price changes compared to discounts across store formats.

The framework illustrates the role of store formats in influencing promotional price effectiveness and moderating how brand and category factors determine brand promotional price effectiveness (i.e., regular price elasticity and discount elasticity). It addresses the following research questions:
(1) How do store formats directly influence the differential effectiveness of regular prices and discounts and moderate the impact of brand factors and category factors on these differential effects?
(2) How do store formats directly influence discounts effectiveness and moderate the impact of brand factors and category factors on the effectiveness of discounts?

To answer these research questions, we explore evidence from academic research suggesting the potential impacts of store formats on promotional price effectiveness and their moderating role in brand and category factors in determining promotional pricing outcomes. Within the scope of brand and category factors, we differentiate between shared and distinct influences. Shared influences, such as discount depth (magnitude), breadth (coverage), are fundamental drivers of promotional effectiveness across both brand and category levels. These factors are directly influ-

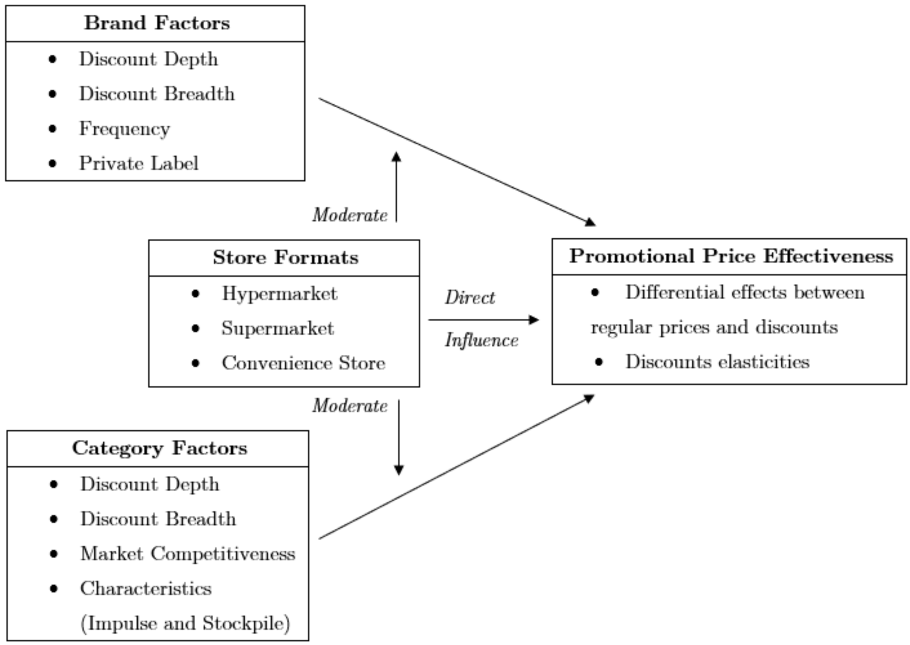

Figure 1: Research Framework

enced by promotional activities, as evidenced by studies like Gauri et al. (2017), which illustrate how broad-based discounting can significantly enhance store traffic and overall sales metrics. On the other hand, distinct factors such as frequency and private label status for brands, or competitiveness and product characteristics for categories, are well-established and commonly referenced determinants of price effectiveness (e.g. Widdecke et al., 2022).

2.2.1 Role of Store Formats in Influencing Regular Price and Discount Effectiveness

While most of the existing research focuses on the overall impact of final prices on sales, there is often a lack of detailed examination of how regular price adjustments and discounts specifically affect brand sales, and how these effects vary across different store formats. It has been documented that effectiveness of promotional pricing strategies often varies across store formats, reflecting differences in consumer shopping goals, preferences, and behaviors associated with each type of retail environment. For example, hypermarkets, supermarkets, and convenience stores within the same retail chain are designed to fulfill distinct needs such as bulk buying, regular grocery shopping, or immediate. These needs can influence how consumers respond to pricing strategies (Koschmann & Isaac, 2018).

Previous research has highlighted these variations in promotional pricing effectiveness, yet much of the focus has been on broader measures such as incremental store sales (Ailawadi et al., 2006) or category sales (Haans and Gijsbrechts, 2011), rather than examining the direct effects of promotional pricing at the brand level and the differential impacts across various store formats. Moreover, the applicability of these broader findings to brand-level sales outcomes, which may exhibit distinct dynamics, remains uncertain. For instance, Jindal et al. (2020) demonstrate that promotional pricing tends to be most effective on brand sales in supermarkets, with a decreasing impact observed in drug stores, mass merchandisers, and convenience stores. This indicates that the effectiveness of price promotions can vary significantly across store types, influenced by the specific consumer shopping behaviors and expectations associated with each format.

The moderating role of store formats has often been examined indirectly, primarily in studies focusing on brand type and category-level factors influencing discount effectiveness. For instance, Widdecke et al. (2022) analyzed promotional effectiveness in supermarkets and discounters, including distinctions between private labels and national brands, but did not differentiate between the effects of regular price adjustments and temporary discounts. Similarly, Van Der Plas et al. (2024) demonstrated that price sensitivity varies between discounters and conventional retailers, particularly for national brands, yet their analysis did not extend to other store formats within the same retailer.

Although private labels and national brands have been studied extensively, limited attention has been given to how brand and category characteristics differently determine promotional price effectiveness across store formats within the same retail chain. The well-documented influence of product-specific factors on pricing effectiveness (e.g., Ailawadi et al., 2006; Gauri et al., 2017) highlights the importance of examining these dynamics across different store formats to provide a deeper understanding of promotional strategies. Store formats not only shape consumer expectations and shopping behaviors but also potentially influence how category characteristics and brand traits affect price-promotional outcomes on brand sales. Exploring these dynamics will illuminate how category- and brand-level factors moderate promotional effectiveness, paving the way for more tailored pricing strategies.

2.2.2 Brand Factors on Promotional Price Effectiveness

There are extensive studies examining how brand factors such as type (private label vs. national brands) and discount characteristics (depth, breadth, and frequency) influence promotional price effectiveness. However, less attention has been given to understanding how these factors separately affect regular prices and discounts across various store formats within the same retail chain.

The nature of the brand itself can determine the effectiveness of promotional pricing strategies. Whether a brand is a private label or a national brand significantly influences consumer price sensitivity. Private labels often elicit higher price sensitivity due to their positioning as value-for-money alternatives, unlike national brands that may benefit from stronger consumer loyalty and perceived quality (Kamakura & Russell, 1989; Krishna et al., 2002; Nijs et al., 2001). Recent research by Van Der Plas et al. (2024) highlights that national brands exhibit greater price sensitivity at hard discounters compared to conventional retailers. However, it is not yet clear whether these effects hold within the same retailer operating across multiple store formats. For example, national brands might experience varying degrees of price sensitivity depending on whether they are sold in hypermarkets, supermarkets, or convenience stores, where consumer expectations and shopping goals differ substantially.

In addition to brand positioning as a private label or a national brand, brand's discount characteristics such as depth, breadth and frequency can influence promotional effectiveness on brand sales. Previous research has shown that deeper and broader discounts are positively correlated with increased consumer purchases and consumption lift (Ailawadi et al., 2006). However, the frequency of discounts (i.e., how often a brand promotes its products) can become influential. Brands that frequently offer discounts may condition consumers to expect them, diminishing their sensitivity to both regular price changes and promotional offers over time (Pauwels et al., 2007; Srinivasan et al., 2004). While these patterns have been documented, it remains unclear whether the relationship between discount strategies and brand characteristics varies across store formats within a single retailer. For instance, private labels might rely heavily on frequent discounting in supermarkets, whereas national brands may need to adopt more tailored discount strategies in hypermarkets or convenience stores to align with format-specific consumer expectations.

2.2.3 Category Factors on Promotional Price Effectiveness

Previous literature has documented how category factors can affect promotional price effectiveness. However, there have been few attempts to understand how these category characteristics vary in their effects across different store formats within the same retail chain. Understanding the moderating role of store formats on category characteristics has significant managerial implications. To effectively implement promotional strategies, retailers have to consider how different category factors interact with store formats to better manage the impact of pricing on brand sales at the category level.

The attributes of product categories can shape consumer reactions to price promotion and influence the effectiveness of promotional prices. Prior research has identified storability and impulsiveness as key category traits that moderate the effects of promotional offers. Narasimhan et al. (1996) and Gauri et al. (2017) emphasize that in storable categories, where products can be easily stockpiled for future use, consumers are more likely to accelerate their purchases during promotions. This stockpiling behavior reflects a strategic response to capitalize on temporary price reductions, resulting in a substantial lift in brand sales during promotional periods, as consumers buy in bulk to save on future costs.

The impact of impulsiveness as a category characteristic on promotional price effectiveness, however, is mixed. Narasimhan et al. (1996) suggest that impulse-buy categories, characterized by spontaneous and unplanned purchases, often display unpredictable responses to price promotions. In these categories, consumer decisions are driven more by emotional triggers than rational price comparisons, potentially reducing the impact on brand sales. Nonetheless, Gauri et al. (2017) provide evidence that even in impulse-buy categories, promotional activities can lead to significant sales increases. Widdecke et al. (2022) further support this, indicating that while consumers in impulse categories may not respond strongly to the magnitude of the discount, they often exhibit heightened sensitivity to the mere presence of a promotional offer, leading to increased purchase behavior.

Apart from category static factors, the category's discount activities, including the category's discount depth and breadth, can shape consumer purchasing behavior. For instance, extensive and deep discounts across a category often lead to increased store traffic, higher sales per transaction, and improved profit margins (Dhar et al., 2001; Gauri et al., 2017). These outcomes suggest that category-wide discounting strategies can be a significant tool for retailers to stimulate demand and enhance overall sales performance.

The competitive landscape within a category is another important determinant of promotional price effectiveness. In highly competitive categories, where numerous brands vie for consumer attention, the impact of price promotions tends to be more pronounced, as consumers become more sensitive to price differences (Srinivasan et al., 2004; Datta et al., 2022). Conversely, in less competitive categories, consumers may exhibit weaker responses to promotions due to limited alternative choices and a reduced tendency to switch brands in response to price changes.

Despite these insights, it remains unclear how these effects vary across store formats within a single retail chain. For example, the effectiveness of promotions in storable categories may be enhanced in hypermarkets due to their larger scale and customer propensity for bulk buying, compared to convenience stores where impulse buying is more common and might not lead to the same volume of stockpiling. This variability suggests a need for retailers to understand format-specific promotional strategies that consider not just the general characteristics of product categories but also how these characteristics influence differently across store formats.

3 Data and Measures

3.1 Empirical Setting

Our study examines the differential effects of regular prices and discounts on brand performance across various product categories in different store formats using detailed scanner data from a Nordic grocery retailer. The dataset covers the period from January 1, 2014, to November 30, 2016 and comes from the retailer's loyalty membership database. The retailer operates under a model, where promotional strategies, such as discount campaigns, are centrally coordinated, but individual store managers retain flexibility in setting regular prices based on local market conditions. This setting creates a unique environment for analyzing pricing strategies, as it allows us to observe how regular prices and promotional discounts interact across different formats while accounting for store-specific implementation.

From the retailer business model, their system has three distinct store formats offered across regions, including a hypermarket, supermarket, and convenience store, each catering to different shopping goals and consumer preferences. The hypermarket is a large hypermarket situated on the outskirts of towns, offering an extensive selection of both grocery and non-grocery items at competitive prices. These stores cater to a larger customer base, focusing on convenience for car-borne shoppers, with a comprehensive assortment and shopping spaces. The supermarket features mid-sized supermarkets providing a broader range of products, emphasizing high service levels and catering to more comprehensive shopping needs. These stores are typically found in residential areas and aim to be the primary grocery destination for local consumers. The convenience stores consist of small, neighborhood stores offering convenient and localized shopping experiences, often located close to residential areas or workplaces. These stores have a limited but tailored assortment focused on everyday essentials and fresh produce, with a strong emphasis on service. By studying these three store formats, we capture a diverse range of consumer behaviors and retail strategies within the same grocery chain.

Store formats in this setting represent standardized retail concepts defined by the retailer, implying structural differences in assortment, pricing strategies, and shopping objectives. While differences in pricing effectiveness could, in principle, arise from store-specific characteristics such as size, assortment, or location, our empirical setting is designed to minimize such variation. We focus on three stores within the same retail chain and geographic area, serving a largely overlapping customer base. As such, format provides a clean and managerially relevant construct to study how consumers respond to pricing and promotions. At the same time, we acknowledge that some residual within-format heterogeneity may remain, and our results should be interpreted as reflecting format-level differences rather than purely store-specific effects.

3.2 Data

3.2.1 Selected Stores

The dataset from the retailer's loyalty membership database includes detailed purchasing information from customers selected through the retailer's loyalty program. It tracks comprehensive shopping behavior, covering who made purchases, the items bought, the timing and quantities of purchases, and the prices paid across all stores within the same retailer chain nationwide. This extensive dataset offers detailed information for analyzing the distinct effects of regular prices and discounts on brand sales across store formats.

Despite the detailed coverage, data at the individual store level can be sparse due to the wide distribution of customer shopping across various locations. This is because the dataset is customer-centric, meaning that store-level observations are inferred from individual shopping behavior rather than directly observed. As a result, many stores are visited only sporadically by the sampled customers, leading to highly sparse store–brand–week observations. To minimize potential geographic and economic disparities and to ensure the quality and continuity of data for our analysis, we focus our analysis on three specific stores, each representing one of the formats (hypermarket, supermarket, and convenience store) located within the same city. These stores were selected because they were frequently visited by a consistent subset of customers from the loyalty program, thus providing a reliable dataset for observing the effects of pricing strategies. Including all stores would introduce substantial noise and discontinuities in the time series, which would complicate the estimation of pricing elasticities that require sufficiently dense and consistent observations over time. Figure 2 illustrates the locations and relative distances of the three store formats, highlighting their proximity within the same area. This geographic focus helps control for external factors, allowing us to isolate the effects of regular pricing and discount strategies across different retail environments.

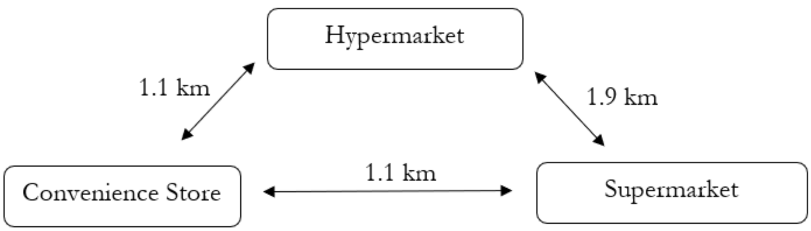

Figure 2: Simple illustration of selected store formats offered by the same retailer chain

We present our initial dataset regarding our empirical setting in Table 2. The data from the retailer's loyalty membership database includes randomly selected 5,468 customers who made total 897,743 grocery shopping trips. Our selected store formats (i.e., hypermarket, supermarket, and convenience store) are significantly different from one another in characteristics and customers' shopping behaviors per trip. Consistent with the described retailer's business model, the three store formats differ significantly in size, assortment, and customer shopping behavior, reflecting their distinct roles within the same retail chain.

The hypermarket, as the largest format (4,252 m^2), offers the widest product assortment, with 1,517 unique brands and 17,400 different products. Shoppers in hypermarkets exhibit the highest average spending per trip (246 SEK), with a broader variety of items purchased, including an average of 10 unique products and 7 brands per visit. The visiting frequency (0.56 trips per week) aligns closely with supermarkets, reflecting their shared role as primary grocery destinations. This trend is consistent with recent survey findings (Statista, 2024), which highlight hypermarkets and supermarkets as top choices among Swedish consumers. Most visits occur on Fridays, likely driven

Table 2: Customers and their spending per trip by store format

	Hypermarket	**Supermarket**	**Convenience**
Size (m^2)	4,252	2,155	497
Total unique brands available	1,517	1,388	680
Total unique products available	17,400	16,026	7,325
Total visitors	5,419	4,499	3,367
Total visits	461,878	314,164	121,701
Avg spending per trip	246	187	110
Avg category per trip	7	6	3
Avg trip per week	0.56	0.46	0.24
Avg unique products per trip	10	7	4
Avg unique brands per trip	7	6	3

Notes: Reported across 897,743 shopping trips from 5,468 customers from the same demographic area visiting these store formats. The table reported the size (square meters), the number of brands and products purchased (units), and the average customers' shopping behaviors in each format per visit. The unit of the spending is in the local currency (SEK).

by preparations for the weekend, while Sundays have the least traffic (Figure 3), possibly due to cultural preferences for relaxation and family time.

The supermarket format, representing a middle ground, features a smaller size (2,155 m^2) and slightly reduced assortment, offering 1,388 unique brands and 16,026 products. The average spending per trip is lower (187 SEK), and customers typically purchase around 7 unique products and 6 brands. This format is strategically positioned to serve local communities as the primary grocery shopping destination, attracting customers with a balanced assortment and a convenient shopping experience. The visiting frequency (0.46 trips per week) and similar visit patterns to hypermarkets (Figure 3) suggest that consumers rely on these formats for their main grocery needs, particularly on Fridays.

The convenience store, being the smallest format (497 m^2), focuses on immediate, essential purchases with a limited but targeted assortment of 680 unique brands and 7,325 products. Customers at convenience stores exhibit the lowest average spending per trip (110 SEK), with fewer items (4 unique products) and brands (3 brands) purchased. The trip frequency (0.24 trips per week) is also the lowest, indicating that consumers use this format primarily for quick, unplanned purchases or emergency needs, aligning with the retailer's strategy of offering accessible, neighborhood-based shopping options. In contrast, convenience stores display a more balanced visit distribution throughout the week, with a noticeable peak on Tuesdays (Figure 3). This suggests that consumers rely on convenience stores for unplanned, urgent purchases or smaller trips. The lower visit percentage on weekends (especially Saturdays) further supports the idea that consumers prefer to visit larger formats when planning their weekly shopping.

Overall, the differences across store formats reflect the retailer's franchise model, where each format is designed to cater to distinct shopping goals and customer preferences. These format

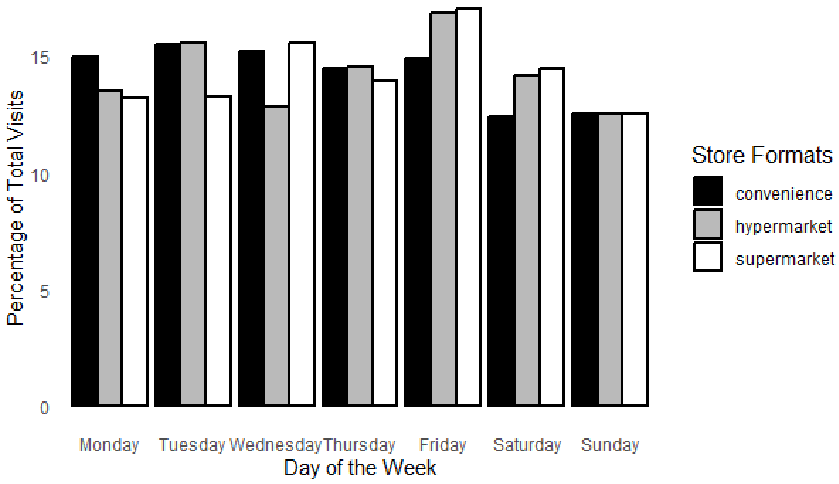

Figure 3: Percentage of Store Format Visits By Day-of-the-Week

distinctions are consistent with the findings by Jindal et al. (2020), who demonstrated that supermarkets and mass merchandisers are frequented for major trips associated with higher spending and broader category purchases. In contrast, convenience stores primarily serve unplanned, urgent trips characterized by smaller baskets and fewer items. Their analysis highlights that consumer responses to marketing-mix variables differ across retail formats, with brand shares being more sensitive to line length changes at convenience stores due to their limited assortments and less frequent trips. This alignment supports the empirical setting of our study, providing an appropriate sample for analyzing how regular pricing and discounts influence brand sales differently across hypermarkets, supermarkets, and convenience stores.

3.2.2 Selected Brand and Category

Given that our dataset comes from the retailer's loyalty membership database, the granularity it offers in terms of customer purchases is significantly more detailed than what is typically available through third-party data (van Heerde and Dekimpe, 2024). Such data allows us to track the same customers who shop across different formats, offering insights into cross-format shopping patterns. However, this detailed level of customer purchasing information from loyalty membership data means we have more limited visibility into the full range of brands offered across all store formats. To address this limitation, we have to carefully select specific brands and categories for analysis that are consistently available across selected hypermarket, supermarket, and convenience store. This approach ensures we capture a sufficient dynamic of pricing strategies and brand performance within each selected store format.

While this method allows for a focused analysis of selected brands and categories, it introduces a potential drawback: the loss of information regarding products and brands that are uniquely tailored or primarily available in specific store formats. Different store formats are often designed to cater to varying consumer needs and preferences, which may mean that some SKUs or product categories are not uniformly available across formats. This selective availability can lead to gaps in our understanding of category and product performance, especially for those items that do not meet our selection criteria due to their limited distribution. Despite this limitation, our focus remains on analyzing the brand performance and pricing strategies effectively within the confines of the available and consistent data across the chosen formats.

First of all, we focus on frequently purchased products (Stock Keeping Unit-level) for each category. We initially selected the top five sizes of each product category that demonstrated high sales volume on a weekly basis. This step is to ensure that comparisons across brands were made between like-for-like products, thereby avoiding inconsistencies that arise from comparing different package sizes. Second, we identify the most frequently purchased products within each category, specifically certain products that are bought at least once every two weeks. These products must have consecutive non-zero sales throughout the entire study period (i.e., 153 weeks), in line with Widdecke et al. (2022), to reduce the risk of noise from sporadic or irregular sales patterns. From the product characteristics identified in the first two steps, we then select those that match in size and have similar product descriptions. This is done to ensure that our comparisons are not only consistent in terms of physical dimensions but also in terms of product description across different brands.

We further focus on frequently purchased brands. We narrow down our selection to include only those brands whose products described earlier are purchased every two weeks across at least two different store formats. This step helps ensure that our analysis can reliably measure how the same brands perform under different format conditions. Lastly, we retain only categories that maintain at least three brands, which are purchased every two weeks across at least two different store formats. This category selection is not only for maintaining sufficient sample sizes for second-stage analysis but also for ensuring that our analysis can capture a range of consumer responses to different brands within the same category across multiple store formats. Moreover, this selection process facilitates interpretation from a retailer's perspective, providing actionable insights into which products and brands could be strategically adjusted in price to enhance sales performance.

Our sample selection process requires scrutinized consideration due to the dataset's characteristics and the multi-format retail environment. While our data does not directly capture store-level data, this information can be inferred from customer transactions. Although inferring store-level data from customer transactions may introduce some variability, this is a well-accepted approach in multi-format retail analysis (e.g., Widdecke et al., 2022; Van Der Plas et al., 2024). As a result of these carefully chosen selection criteria, we retained a dataset used for the analysis comprising 233,456 weekly shopping trips from 5,384 customers. This final sample includes 55 unique brands across 14 frequently purchased categories[1] (Table 3). While our final dataset focuses on 55 unique brands across 14 categories for examining price and discount elasticities, it is important to note that there are total 66 unique brands whose products frequently purchased. These 11 additional brands are used to construct competitor's price information within the analysis. However, they do not meet the criteria for inclusion as focal brands in our elasticity study because they are not purchased consistently across more than two store formats.

Table 3: Focal Categories and Brands Included in This Study

Store Format	Hypermarket	Supermarket	Convenience
Total Unique Visitors	5,193	4,176	2,743
Total Sales	16,853,451	8,557,788	1,525,896
Number of Focal Category	14	14	13
Number of Focal Brand: Baking	3	3	1
Number of Focal Brand: Berries	3	3	2
Number of Focal Brand: Bottled water	3	3	3
Number of Focal Brand: Butter	9	9	5
Number of Focal Brand: Cereals	5	5	-
Number of Focal Brand: Chips	3	3	3
Number of Focal Brand: Chocolate	4	4	2
Number of Focal Brand: Cream	6	6	4
Number of Focal Brand: Fruit Juice	10	10	3
Number of Focal Brand: Ice cream	5	5	3
Number of Focal Brand: Milk	3	3	1
Number of Focal Brand: Pasta	5	5	3
Number of Focal Brand: Soft drinks	8	8	6
Number of Focal Brand: Toiletries	4	4	2

Notes: The table reports sales value in local currency.

3.2.3 Example of Selection Process

To demonstrate our selection process, we provide an example of how category of soft drinks is selected. In our dataset, soft drinks are purchased by customers in our loyalty program across a variety of store formats and locations, including occasional purchases in stores outside of their usual shopping area, such as during trips to the capital city. These variations introduce significant price disparities and shopping behaviors, complicating the analysis of pricing strategies and brand performance. To mitigate these complications, we focused on selecting stores located in the city where our customers reside and shop regularly so we could compare shopping behaviors across consistent geographic and economic conditions and across different store formats—hypermarkets, supermarkets, and convenience stores.

The variety of packaging for soft drinks ranges widely, from large 3-liter bottles to packs of 20 small cans. Such diversity in product sizes and types can skew straightforward comparisons. Therefore, to maintain comparability across store formats, we selected specific product sizes that

[1]These categories include: Baking ingredients, Berries, Bottled water, Butter, Cereals, Chips & Salty snacks, Chocolate, Cream, Fruit Juice, Ice cream, Milk, Pasta, Soft drinks, Toiletries.

are commonly available and frequently purchased across all three store formats. We chose to focus on sugary carbonated drinks, a popular sub-category within soft drinks, and standardized the product sizes for analysis: 330ml cans, 500ml normal bottles, and 1500ml big bottles. These sizes are prevalent across all formats, ensuring a fair comparison. Additionally, to facilitate more accurate comparisons and analysis, all package sizes were converted into units of 100ml. This conversion allows us to normalize the data, making it possible to compare pricing and quantity across different package sizes effectively.

Observing customer purchases over 153 weeks (i.e., 77 biweekly times), seasonal and festive-specific products, such as specialty soft drinks that are heavily purchased during specific periods (e.g., Christmas), pose a challenge. These products, while significant in volume during certain times, do not represent regular purchasing patterns throughout the year. Including such items could distort the analysis of regular price sensitivity and discount effectiveness. Consequently, we exclude products that are not consistently purchased throughout the study period of 153 weeks. By doing so, we focus on those brands and products that exhibit stable sales, providing a more accurate reflection of ongoing consumer behavior and brand performance.

3.3 Variable Operationalization

3.3.1 First-stage variables

In the first-stage analysis, we quantify the effects of regular prices and discounts on brand performance (i.e., brand sales in unit) by estimating their elasticities. We aggregate customer purchase data from the retailer's loyalty membership database to the weekly brand level for each store format. To ensure accuracy in our estimates, we aggregate customer purchase data from the retailer's loyalty membership database to the weekly brand level for each store format. This aggregation is made possible by our selection process, which ensures that the products and brands included in our dataset are consistently purchased across all selected store formats, thereby providing reliable measures of aggregated brands' prices and performance data. Table 5, Panel A provides details about the operationalization of the variables in the first-stage analysis.

The dependent variable in our analysis is the weekly brand volume sales. To estimate the elasticities, we employ the sales-response model proposed by Pauwel et al. (2007) having brand price (i.e., regular price and discounts), competitor brands price, and non-price promotion as independent variables. Since we are interested in changes of sales across format, we control for additional variations, apart from the seasonality, that might affect sales independently of price changes.

First, we include category visits, the number of customers in the loyalty membership database visiting the selected store in a given period to buy products in a given category. This variable accounts for the average traffic each category receives across different store formats. Higher traffic can often lead to variations in sales figures, which are independent of our primary variables of interest, such as price changes.

Second, we include average share of trip types. Following the methodology outlined by Jindal et al. (2020), we construct trip types using initial transaction data including baskets of all brands and categories. We analyze characteristics of the basket or receipt as follows. Trips were categorized as 'major' if their spending levels, number of items purchased, or number of product categories exceeded the median values for each customer. We then employ K-means clustering to further classify the non-major trips into 'fill-in' and 'unplanned minor' trips based on the following basket characteristics: average price per item, number of items and categories purchased, the number of days since the last trip to account for intershopping times [2]. We report the average trip characteristics per trip per household by their trip type in in table 4. To address potential issues of collinearity—which could arise because the shares of trip types sum to one—we selectively include only the share of major trips and the share of unplanned minor trips in our analysis.

Table 4: Average Statistics (Per Trip) by Trip Type

	Major	**Fill-in**	**Unplanned Minor**
Average Price Per Item	25	17	24
Average Total Items Purchased	16	5	2
Average Total Categories Purchased	9	4	2

Notes: Reported average trip characteristics per trip per household across 904,619 trips made by 5,435 households from anuary 1, 2014, to November 30, 2016.

The rationale for including trip type as an additional control variable is to control for observed potential relation between shopping trip characteristics and store format, and self-selection bias. The empirical setting described in section 3.2.1 implies distinct patterns related to each store format—such as average spending per trip, the typical number of categories per trip, and the assortment of products purchased. These patterns suggest that trip characteristics might vary systematically across formats, influencing sales independently of price changes. These observed patterns correspond to the trip type classifications outlined by Jindal et al. (2020). Controlling for trip types helps mitigate potential self-selection bias, where customers in the loyalty program may choose a particular store format based on specific needs or shopping goals. Without accounting for these trip types, our analysis could incorrectly attribute differences in sales performance to pricing strategies rather than to the underlying shopping intent and store format preference.

3.3.2 Second-stage variables

In the second-stage analysis, we aim to quantify systemic differences in the effectiveness of regular pricing and discounts across different store formats, and explore the role of store formats

[2]Following Jindal et al. (2020), we standardize these variables at the house-hold level to ensure that trips are clustered on the basis of within-household differences.

in influencing how brand and category factors determine these price elasticities. According to our research framework, brand factors include brand's discount depth, brand's discount breadth, brand's discount frequency and whether the brand is a private label. Category factors include category's discount depth, category's discount breadth, category's market competitiveness. For category characteristics (i.e., impulsiveness and storability), we use the scale from the data employed in Gauri et al. (2017) and a consumer survey conducted in 2020 by a marketing research company in The Nordics. Table 5, Panel B provides details about the operationalization of the variables in this second-stage analysis.

Table 5: Variable Operationalization

Variable	**Operationalization and Description**
Panel A: Variables in First-Stage Sales-Response Model	
$\text{Sales}_{ijk,t}$	Unit sales for brand i in category j in store format k in week t.
$\text{RegPrice}_{ijk,t}$	Regular price of brand i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in local currency.
$\text{Discount}_{ijk,t}$	Discounts offered of brand i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in local currency.
$\text{FD}_{ijk,t}$	Intensity of feature and/or display support for brand i in category j in store format k in week t, computed as a sales-weighted average across its SKUs sold in period t, expressed in number range from 0 to 1.
$\text{CompPrice}_{ijk,t}$	Sales-weighted average of brands i's competing brands' ($\neq i$) average price paid in category j in store format k in week t.
$\text{CVisitors}_{jk,t}$	Total number of customers made purchase in category j in store format k in week t.
$\text{ShareMajor}_{ijk,t}$	Average share of Major Shopping Trip made for brand i in category j in store format k in week t.
$\text{ShareUnplan}_{ijk,t}$	Average share of Unplanned Shopping Trip made for brand i in category j in store format k in week t
Panel B: Variables in Second-Stage Regression	
Brand Factors	
BDepth_{ijk}	Average weekly ratio of discounts to regular prices of brand i in category j in store format k.
BBreadth_{ijk}	Average weekly ratio of number of SKUs getting promoted to total number of SKUs of brand i in category j in store format k.
BFreq_{ijk}	Ratio of number of weeks in which negative price-promotion shocks are at least 5% of the brand i's regular price to total number of weeks in the study in category j in store format k
PL_{ij}	An indication variable equal to 1 if brand i in category j is owned by the retailer.
Category Factors	
CDepth_{jk}	Average weekly ratio of discounts to regular prices of category j in store format k.
CBreadth_{jk}	Average weekly ratio of number of SKUs getting promoted to total number of SKUs of category j in store format k.
CComp_{jk}	Variance in shares across brand of category j in store format k
Impulse_{j}	An indication variable equal to 1 if category j is impulsive (scale reported by Gauri et al. (2017) and the survey
Storable_{j}	An indication variable equal to 1 if category j is storable (scale reported by Gauri et al. (2017) and the survey

3.4 Descriptives

Table 6 presents descriptive statistics for our variables across different store formats within our dataset. The hypermarket generally exhibits the lowest average regular prices and the greatest standard deviations in prices, indicating a broader range of prices available compared to other formats. In terms of discounts, while the average discount per-unit discounts across brands and categories tends to be relatively low, the hypermarket still displays relatively highest discount as well as the standard deviations. Conversely, the convenience store tends to have higher average regular prices across many categories, which could be attributed to their focus on convenience and immediate accessibility. Additionally, the convenience store engages less frequently in discount activities at both brand and category level. The supermarket, positioning between hypermarkets and convenience stores, shows a moderate level of pricing and discount activity. Overall, the behavior of pricing and discounting of our selected stores, brands and formats aligns with the retailer business model.

In addition to pricing and discounting which are key interests, our study controls category visits and the distribution of trip types across store formats. The hypermarket tends to attract a larger volume of visits and a higher proportion of major shopping trips. This aligns with their role as destinations for extensive, planned shopping activities. On the other hand, the convenience store records a greater share of unplanned trips, highlighting their role in catering to immediate, spontaneous needs. The supermarket, with their moderate visitor counts, frequently host both planned and unplanned trips (and fill-in trips), illustrating their versatile shopping environment.

4 Model-free evidence

We start by providing model-free evidence for our research framework in proposing the role of store format in influencing how brand and category factors determine brand promotional price effectiveness (i.e., regular price elasticity and discount elasticity). In this section, we focus on the bottled water category as an example for model-free evidence. We select one national brand and one private label to investigate the relationship between changes in regular price and discount with respect to unit sales across different store formats. Figures 4 and 5 visually depict how sales volume responds to changes in regular prices and discounts for the national brand and private label respectively.

The plots illustrate that the relationship between promotional price (i.e., regular prices and discounts) changes and sales volume varies not only across formats but also between the national brand and the private label. Notably, for a given change in regular price, the slope of the response curve differs across store formats, indicating that the impact of price adjustments on sales volume is potentially influenced by the type of store. This variation suggests that consumer sensitivity to price changes might be different in the hypermarket compared to the supermarket and the

Table 6: Descriptives Statistics

	Hypermarket	**Supermarket**	**Convenience**
Variables in First Stage: RegPrice and Discount			
Brand RegPrice: Baking	10.11 (1.32)	10.95 (1.18)	10.60 (1.76)
Brand RegPrice: Berries	6.68 (1.88)	7.26 (2.28)	7.03 (2.52)
Brand RegPrice: Bottled water	0.83 (0.08)	0.88 (0.14)	1.05 (0.25)
Brand RegPrice: Butter	4.02 (1.21)	4.23 (1.24)	4.17 (1.44)
Brand RegPrice: Cereals	6.41 (1.45)	6.60 (1.45)	-
Brand RegPrice: Chips & Salty snacks	7.02 (0.71)	6.79 (1.18)	7.84 (1.29)
Brand RegPrice: Chocolate	13.60 (5.16)	15.43 (4.18)	14.31 (1.62)
Brand RegPrice: Cream	3.81 (0.44)	3.83 (0.38)	4.61 (1.04)
Brand RegPrice: Fruit Juice	1.66 (0.70)	1.72 (0.71)	1.83 (0.28)
Brand RegPrice: Ice cream	3.27 (3.23)	3.65 (3.14)	2.27 (0.59)
Brand RegPrice: Milk	0.90 (0.10)	0.96 (0.14)	1.33 (0.53)
Brand RegPrice: Pasta	1.81 (0.39)	1.75 (0.43)	1.96 (0.36)
Brand RegPrice: Soft drinks	1.14 (0.17)	1.35 (0.30)	1.45 (0.39)
Brand RegPrice: Toiletries	25.38 (7.79)	26.16 (7.43)	27.76 (8.71)
Brand Discount: Baking	0.14 (0.22)	0.11 (0.18)	0.20 (0.37)
Brand Discount: Berries	0.19 (0.37)	0.19 (0.40)	0.26 (0.62)
Brand Discount: Bottled water	0.02 (0.03)	0.02 (0.03)	0.03 (0.03)
Brand Discount: Butter	0.08 (0.16)	0.10 (0.22)	0.07 (0.21)
Brand Discount: Cereals	0.08 (0.11)	0.06 (0.12)	-
Brand Discount: Chips & Salty snacks	0.34 (0.49)	0.18 (0.23)	0.11 (0.24)
Brand Discount: Chocolate	1.04 (1.55)	0.46 (1.22)	0.39 (0.92)
Brand Discount: Cream	0.10 (0.15)	0.12 (0.18)	0.10 (0.27)
Brand Discount: Fruit Juice	0.05 (0.07)	0.04 (0.05)	0.04 (0.07)
Brand Discount: Ice cream	0.06 (0.14)	0.11 (0.28)	0.09 (0.23)
Brand Discount: Milk	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
Brand Discount: Pasta	0.07 (0.12)	0.05 (0.13)	0.07 (0.18)
Brand Discount: Soft drinks	0.08 (0.06)	0.08 (0.07)	0.09 (0.12)
Brand Discount: Toiletries	0.76 (1.23)	0.63 (1.24)	0.62 (1.73)
Variables in First Stage: Category Visits and Share of Trip Types			
CVisitors	875.60 (656.87)	437.60 (326.57)	104.76 (80.12)
ShareMajor	0.89 (0.07)	0.84 (0.10)	0.51 (0.17)
ShareUnplan	0.03 (0.04)	0.04 (0.05)	0.18 (0.13)
Variables in Second Stage: Brand Factors			
BDepth	0.033 (0.024)	0.029 (0.020)	0.030 (0.020)
BBreadth	0.041 (0.037)	0.039 (0.033)	0.030 (0.032)
BFreq	0.209 (0.215)	0.187 (0.177)	0.306 (0.218)
Variables in Second Stage: Category Factor			
CDepth	0.033 (0.027)	0.025 (0.015)	0.021 (0.019)
CBreadth	0.232 (0.093)	0.212 (0.093)	0.120 (0.048)
CComp	0.041 (0.041)	0.0035 (0.041)	0.040 (0.046)

Notes: The table reports the mean price per unit (SD) across 180 brands and their factors, as well as the mean variables of category factors (SD) across 14 categories, aggregated over 233,456 shopping trips by 5,384 customers in the same demographic area. These figures are averages calculated over 77 biweekly periods.

convenience store. When comparing the response to price changes between the national brand and the private label within the same format, we observe distinct patterns. The national brand tends to show a more pronounced change in sales volume for similar price changes compared to the private label. However, in the convenience store, the effect of price changes and discounts for the national brand appears to be symmetrical, suggesting that reductions in regular price and increases in discounts have similarly proportional effects on sales volume.

In principle, if changes in regular price and discounts had symmetrical effects on sales, the relationship depicted would mirror each other. This means that a decrease in regular price would have a comparable impact to an equivalent increase in discount. For example, in convenience stores, one might expect that price reductions and increases in discounts would have similar effects on sales volumes. However, the figures illustrate that this is not always the case; for instance, the relationship shown in figure 5 for the private label in hypermarkets reveals that sales volumes increase significantly with discounts but do not decrease equivalently with similar increases in regular prices. This asymmetry implies that consumers may perceive and react to price decreases and discount increases differently. These empirical observations suggest that store formats influence how pricing strategies affect sales.

5 Method

In this study, we examine the differential effects between regular prices and discounts on brand performances offered across different categories in different store formats. We also investigate the potential determinants of discount effectiveness from brand and category factors and compare them across store formats. In line with previous studies (e.g., Datta et al., 2022), we first estimate regular price and discount elasticities across 55 brands using sales-response models. We then estimate a regression with respect to (1) the differences of elasticities and (2) discount elasticities using brand and category factors and store formats (i.e., hypermarket, supermarket and convenience store) as moderators.

5.1 Sales-Response Model Specification

In order to quantify the effect of regular prices and discounts, we adopt an error correction specification. This specification allows us to estimate the short-run elasticity of price and discount while accounting for potential long-run equilibrium relationships (Pauwels et al., 2007). In our sales response model specification, we use linear model to avoid the potential aggregation bias that might happen in other specifications such as log-log specification (Datta et al., 2022). Moreover, the linear model provides straightforward interpretation of the coefficients. For instance, the coefficient of the discount can be interpreted such that a change of one unit in the local currency of the discount leads to an estimated change in unit sales. This interpretation is direct and does

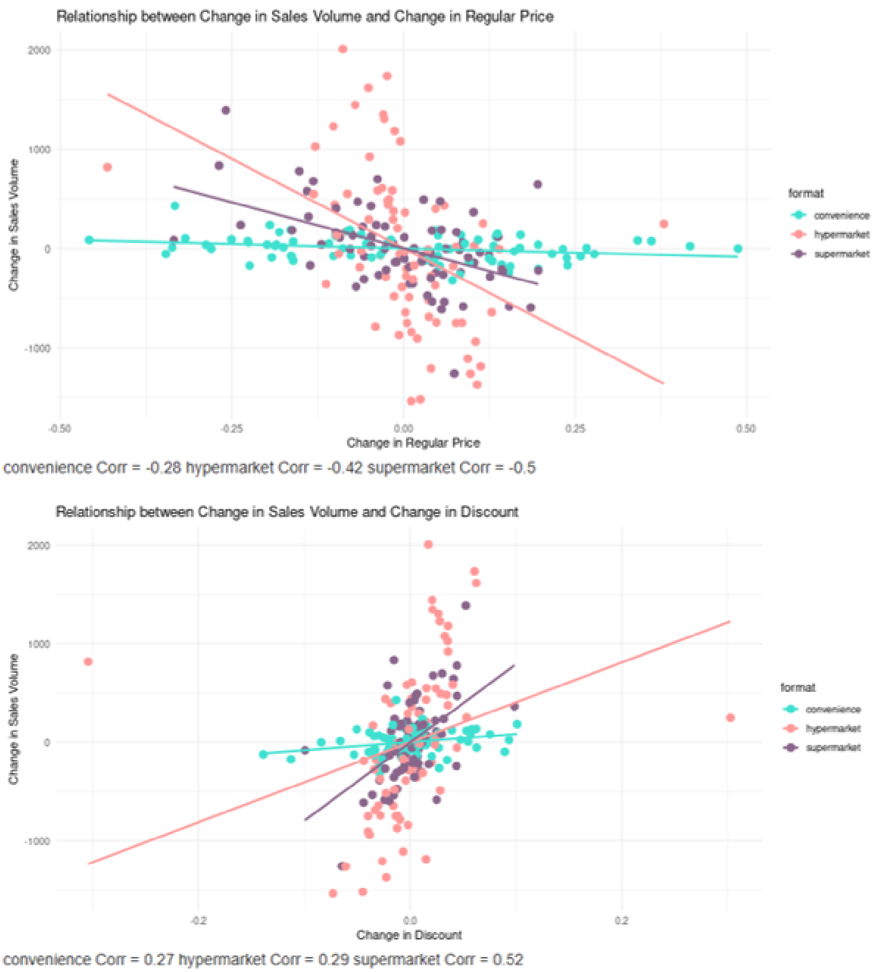

Figure 4: A scatter plot of time series of the changes in sales (100ml) of bottled water with respect to the changes in regular price and discount (per unit) and their correlations for national brand across formats

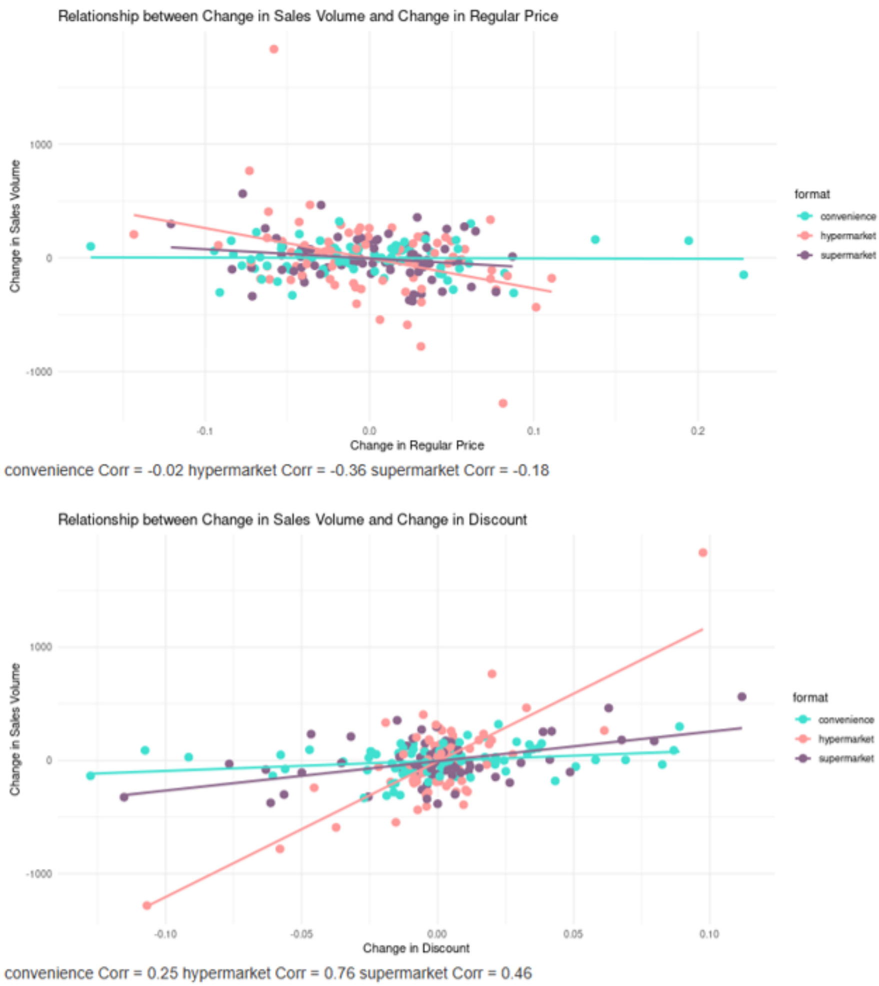

Figure 5: A scatter plot of time series of the changes in sales (100ml) of bottled water with respect to the changes in regular price and discount (per unit) and their correlations for private label across formats

not require further transformation, making it easy to understand the impact of price changes and discounts on sales.

Adopting an error-correction specification, the model for brand sales i in category j in store format k is:

$$\begin{aligned}(1)\quad \Delta S_{ijk,t} = {} & \beta_0 + \beta_{1ijk}\Delta RegPrice_{ijk,t} + \beta_{2ijk}\Delta Discount_{ijk,t} \\ & + \beta_{3ijk}\Delta CompPrice_{ijk,t} + \beta_{4ijk}FD_{ijk,t} \\ & + \gamma_{ijk}[S_{ijk,t-1} - \alpha_{0ijk} - \alpha_{1ijk}RegPrice_{ijk,t-1} - \alpha_{2ijk}Discount_{ijk,t-1}] \\ & + \beta_{5ijk}CVisitors_{jk,t} + \beta_{6ijk}ShareMajor_{ijk,t} + \beta_{7ijk}ShareUnplan_{ijk,t} \\ & + \beta_{8ijk}Holiday_t + \beta_{9ijk}Week_t + \beta_{11ijk}Year_t \\ & + \beta_{11ijk}CopulaRegPrice_{ijk,t} + \beta_{12ijk}CopulaDiscount_{ijk,t} + \varepsilon_{ijk}\end{aligned}$$

where $\Delta X_t = X_t - X_{t-1}$ indicates the first difference of variable X, emphasizing changes rather than levels to address potential non-stationarity in time series data. The coefficients $\hat{\beta}_{1ijk}$, $\hat{\beta}_{2ijk}$, $\hat{\beta}_{3ijk}$ and $\hat{\beta}_{4ijk}$ capture the immediate impact of changes in regular price, discount, competitors' prices, and brand's feature and display, respectively, on the sales volume. The error-correction term represented by γ_{ijk} measures how quickly sales revert to equilibrium following a change in regular prices and discounts, highlighting the dynamic adjustment process. Additional controls including category-specific visits in each store format ($CVisitors_{jk,t}$) and average shares of shopping trip types ($ShareMajor_{ijk,t}$,$ShareUnplan_{ijk,t}$) are introduced in the model. Seasonal effects are controlled through dummy variables for holidays, weeks, and years to ensure the model captures any systematic variations specific to these periods. In addition to variables of interest, we added the Gaussian copula for $RegPrice_{ijk,t}$ and $Discount_{ijk,t}$ to address the potential presence of endogeneity (e.g., endogeneity caused by idiosyncratic changes in consumer preferences for brands) (Datta et al., 2022).

In this error-correction model, we obtain short-term effects for regular price ($\hat{\beta}_{1ijk}$) and discount ($\hat{\beta}_{2ijk}$) on sales for each brand. These coefficients represent the change in sales units for a one-unit change in price or discount (in local currency). However, given that different categories have different units of sales, we control for scale differences by converting the obtained parameters ($\hat{\beta}_{1ijk}$, $\hat{\beta}_{2ijk}$) to unit-free elasticities. This is done by normalizing the estimated parameters with the ratio of the sample mean[3] of promotional price of each brand (i.e., regular price and discount)

[3]Since we observe irregular drops of regular prices in certain products, we use the sample median instead of mean to avoid the extreme values in time-series.

to sample mean of sales of each brand (Srinivasan et al., 2004; Datta et al., 2022). Thus we get,

$$\hat{\eta}_{1ijk} = \hat{\beta}_{1ijk} * \frac{(\overline{RegPrice}_{ijk})}{(\overline{Sales}_{ijk})}$$

$$\hat{\eta}_{2ijk} = \hat{\beta}_{2ijk} * \frac{(\overline{Discount}_{ijk})}{(\overline{Sales}_{ijk})}$$

where $\hat{\eta}_{1ijk}$ is the estimated regular price elasticity at mean and $\hat{\eta}_{2ijk}$ is the estimated discount elasticity at mean. We then define a differential effect between regular price and discount for brand sales i in category j in store format k as $\hat{\eta}_{1ijk} + \hat{\eta}_{2ijk}$ [4]. We obtain standard errors for estimated regular price elasticity and estimated discount elasticity using the delta method (Greene 2003). For differential effect between regular price and discount, we obtain $SE(\hat{\eta}_{1ijk} + \hat{\eta}_{2ijk}) = \sqrt{Var(\hat{\eta}_{1ijk}) + Var(\hat{\eta}_{2ijk}) + 2Cov(\hat{\eta}_{1ijk}, \hat{\eta}_{2ijk})}$.

The differential effect is calculated to understand the relative impact of regular prices and discounts on sales (at mean) within different store formats and product categories. For instance, if the sum of the elasticities approaches zero, it would indicate that the impact of a regular price increase can be attenuated by an equivalent discount, suggesting a symmetric sensitivity to both pricing strategies. Conversely, a significant deviation from zero in this differential effect could highlight an asymmetry in sales responses to price increases versus discounts, which may vary by store format and category. A positive differential effect indicates that discounts more effectively boost sales than regular price increases diminish them, suggesting discounts have a stronger influence. On the other hand, a negative differential effect implies that regular price increases suppress sales more significantly than discounts can enhance them, reflecting heightened price sensitivity. This hypothesis is based on the assumption that the economic impact of a price increase equals an equivalent discount, thereby leading to a symmetrical effect on sales volume across different store formats and categories. To test this assumption, we conduct a linear hypothesis test to determine if the sum of the estimated coefficient of regular price ($\hat{\beta}_{1ijk}$) and discount ($\hat{\beta}_{2ijk}$) is statistically equal to zero.

5.2 Second-Stage Regression

In the second-stage analysis, we estimate the following regressions for differential effect between regular price and discount ($\hat{\eta}_{1ijk} + \hat{\eta}_{2ijk}$) and discount elasticity ($\hat{\eta}_{2ijk}$) for brand i in category j

[4]Given our research framework, which posits that store formats may influence the relative effectiveness of regular prices and discounts, we hypothesize that the effects of price increases (regular price elasticity) and price reductions (discount elasticity) should ideally offset one another, resulting in a combined sum of these elasticities approaching zero.

offered in store format k:

$$
\begin{aligned}
(2)\quad \hat{\eta}_{1ijk} + \hat{\eta}_{2ijk} = & \sum_{k=1}^{3} \delta_{0k} Format_{ijk} \\
& + \sum_{k=1}^{3} \delta_{1k} Format_{ijk} * BDepth_{ijk} + \sum_{k=1}^{3} \delta_{2k} Format_{ijk} * BBreadth_{ijk} \\
& + \sum_{k=1}^{3} \delta_{3k} Format_{ijk} * BFreq_{ijk} + \sum_{k=1}^{3} \delta_{4k} Format_{ijk} * PL_{ij} \\
& + \sum_{k=1}^{3} \delta_{5k} Format_{ijk} * CDepth_{jk} + \sum_{k=1}^{3} \delta_{6k} Format_{ijk} * CBreadth_{jk} \\
& + \sum_{k=1}^{3} \delta_{7k} Format_{ijk} * CComp_{jk} + \sum_{k=1}^{3} \delta_{8k} Format_{ijk} * Impulse_{j} \\
& + \sum_{k=1}^{3} \delta_{9k} Format_{ijk} * Storable_{j} + \upsilon_{ijk}
\end{aligned}
$$

$$
\begin{aligned}
(3)\quad \hat{\eta}_{2ijk} = & \sum_{k=1}^{3} \kappa_{0k} Format_{ijk} \\
& + \sum_{k=1}^{3} \kappa_{1k} Format_{ijk} * BDepth_{ijk} + \sum_{k=1}^{3} \kappa_{2k} Format_{ijk} * BBreadth_{ijk} \\
& + \sum_{k=1}^{3} \kappa_{3k} Format_{ijk} * BFreq_{ijk} + \sum_{k=1}^{3} \kappa_{4k} Format_{ijk} * PL_{ij} \\
& + \sum_{k=1}^{3} \kappa_{5k} Format_{ijk} * CDepth_{jk} + \sum_{k=1}^{3} \kappa_{6k} Format_{ijk} * CBreadth_{jk} \\
& + \sum_{k=1}^{3} \kappa_{7k} Format_{ijk} * CComp_{jk} + \sum_{k=1}^{3} \kappa_{8k} Format_{ijk} * Impulse_{j} \\
& + \sum_{k=1}^{3} \kappa_{9k} Format_{ijk} * Storable_{j} + \phi_{ijk}
\end{aligned}
$$

where k is an indication of the store format ($k = 1$ is Hypermarket, $k = 2$ is Supermarket and $k = 3$ is Convenience Store). $\sum_{k=1}^{3} \delta_{0k}$ and $\sum_{k=1}^{3} \kappa_{0k}$ indicate direct effects of store formats on differential effect between regular price and discount and discounts elasticity while $\sum_{n=1}^{9} \sum_{k=1}^{3} \delta_{nk}$ and $\sum_{n=1}^{9} \sum_{k=1}^{3} \kappa_{nk}$ suggest moderating effects of store formats on brand factors and category factors. To account for uncertainty in the elasticity estimate, we estimate model (2) and (3) with weights equal to the inverse standard errors of the elasticity estimates (Datta et al., 2022).

Model (2) examines the combined effect of changes in regular prices and discounts on sales at mean ($\hat{\eta}_{1ijk}+\hat{\eta}_{2ijk}$), aiming to capture how the impact of regular price adjustments and discounting strategies together deviate from zero. The independent variables include store format indicators and their interactions with brand and category factors such as discount depth, discount breadth, discount frequency, private label status, and category competitiveness. The specification allows us to explore how these factors modify the combined impact of pricing strategies across different retail environments. It is worth noting that the potential zeros in differential effects ($\hat{\eta}_{1ijk} + \hat{\eta}_{2ijk}$) do not necessarily signify a lack of data variability or diminish the validity of our models. In our analysis, zeros in the differential effect can indicate instances where the price increase and discount effects are symmetrical, leading to a net zero effect on sales. For example, high variability in the discount depth or frequency among different store formats can help us understand why some formats may see more substantial deviations from zero in the differential effect, indicating more aggressive or effective discounts offered.

Model (3) focuses specifically on the elasticity of discounts ($\hat{\eta}_{2ijk}$), assessing how responsive sales are to changes in discounts within each store format. By incorporating interactions of store formats with brand and category characteristics, these models are specified to identify how different retail environments influence the effectiveness of discounts.

6 Results

6.1 Elasticities Across Store Formats

We report the summary of the first stage analysis (by format) in table 7. In addition to model (1) specified in section 5, we simply run the model with only final price (i.e., $RegPrice + Discount$) as a baseline to compare the estimates and model fits with model (1). When the final price is considered as a single variable, its elasticity appears larger, suggesting a potential overestimation of overall price sensitivity compared to analyzing the separated effects of regular price and discount. Although the error correction models provide relatively good model fits, evidenced by comparable Adjusted R^2 values, it remains inconclusive whether the model that separate the effects of both regular price and discount performs significantly better than the model capturing only the total effect of the final price. The similar Adjusted R^2 values, which account for the number of predictors used, suggest that both models explain a similar proportion of the variance in sales, adjusted for the complexity of each model.

The estimated average of regular price elasticity across all store formats has a significant negative effect, with elasticity values ranging from -4.46 in the hypermarket to -2.74 in the convenience store. The magnitude of this elasticity is more pronounced in the hypermarket (i.e., 1% increase in regular price from mean lead to 4.25% decrease in sales).

The estimated average of discount elasticity shows a significant positive effect across all formats, with the hypermarket exhibiting the most substantial response (9.63), followed by the supermarket (5.87) and the convenience store (1.94). The varying degrees of responsiveness across formats highlight the differential impact of promotional activities, suggesting that while discounts can boost sales, the extent of their impact can vary depending on the store type.

The differential elasticity, suggesting the combined effect of change in regular prices and dis-

Table 7: Summary Statistics for Estimated Price Elasticities and The Difference Between Regular Price and Discount Elasticity of Focal Brand and Category by Store Format

	Hypermarket	**Supermarket**	**Convenience**
N	71	71	38
Final Price Elasticity			
Mean^a	-7.29***	-5.71***	-2.95***
%Pos	1	1	3
%Neg	80	70	66
%n.s.	18	28	31
Regular Price Elasticity			
Mean^a	-4.46***	-2.79***	-2.74***
%Pos	2	0	5
%Neg	73	52	58
%n.s.	24	48	37
Discount Elasticity			
Mean^a	9.63***	5.87***	1.94***
%Pos	75	65	61
%Neg	0	1	0
%n.s.	24	35	39
Differential Elasticity			
Mean^a	-4.27***	-2.64***	-2.72***
$\%s.^b$ for $\hat{\beta}_{1ijk} + \hat{\beta}_{2ijk} = 0$	76	65	61
Model Fit			
R^2 for Final Price Model	0.81	0.77	0.77
R^2 for Reg Price and Discount Model	0.81	0.77	0.78

a: Two-sided tests of significance. Elasticities are weighted by inverse standard errors. Significance tested (at p < .10) using meta-analytic p-value (method of added Zs) (Datta et al., 2022).
b: The linear hypothesis test of equality of regression coefficients ($\hat{\beta}_{1ijk}$ = -$\hat{\beta}_{2ijk}$). Significance tested (at p < .10) using Wald test.
Notes: Reported average of elasticies (standard errors) across 166 brands across 14 categories. The column "%Pos" ("%Neg") shows the percentage of estimated elasticities that are significant and positive (negative) in magnitude. The column "%n.s." reports the share of estimated elasticities that is not significantly different from zero ($p \geq .10$). The reported average R^2s are Adjusted R^2s that penalize the addition of parameters. Note that the elasticity estimates for 14 brands have been excluded from the analysis. This exclusion is due to a small number of discounts for these brands, which leads to singularities in the regression model.

counts, shows significant negative values across all formats, from -4.27 in the hypermarket to -2.72 in the convenience store. The negative differential effects suggest that the impact of regular price increases generally outweighs the positive effects of discounts. Despite the higher average discount elasticity, the combined effect, when considering the relative weights of regular price and discount changes, shows that regular price increases tend to dominate. In other words, the negative effect of regular price increases slightly outweighs the positive effect of discounts in the weighted average calculation. It is worth noting that about half of the brands in this study exhibit a sum of the estimated coefficients of regular price and discount that is statistically not equal to zero. This finding addresses that the effects of price increases and discounts are not symmetric requiring the separate analysis between regular prices and discounts to fully understand their distinct impacts on sales.

The histograms of estimated elasticities for regular price and discount are also presented in figure 6 and 7 respectively. The presented estimates are standardized estimates which take into account the standard error of the estimates. The histograms of estimated price elasticities provide insights into the differential impacts of price changes on brand sales across different store formats. The empirical estimates indicates the shapes of these distributions to be asymmetric across formats. Regular price elasticity predominantly exhibits negative values, with hypermarket showing a particularly strong negative response, indicating a significant sensitivity to price increases. Discount elasticity shows positive values, suggesting a robust responsiveness to promotional pricing, with the hypermarket again displaying the most pronounced positive responses. Both convenience store and supermarket exhibit distributions that are more centered around zero, suggesting a more moderate response to price changes and discounts compared to the hypermarket.

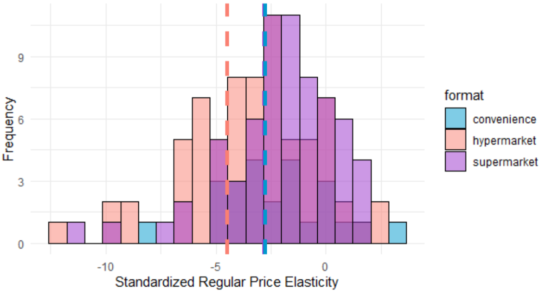

Figure 6: Histogram of Standardized Regular Price Elasticity with Weighted Average by Format (Vertical Line)

Figure 7: Histogram of Standardized Discount Elasticity with Weighted Average by Format (Vertical Line)

6.2 Differential Effects between Regular Prices and Discounts

We examine how store formats influence brand and category factors in determining brand promotional price effectiveness (i.e., the difference between regular price elasticity and discount elasticity) and discount effectiveness (discount elasticity). We report the results of the second-stage analysis in Table 8.

While there is no main effect of store formats on discount elasticity, significant effects on the differential effects between regular price and discount are found in the convenience store (which is the intercept) and supermarket. The large magnitude of negative intercept implies that the effects of changes in regular prices are significantly more pronounced than the same amount of changes in discounts across all formats (since $\hat{\beta}_{1ijk} + \hat{\beta}_{2ijk} < 0$). The positive coefficient for the supermarket suggests that the differential effects in the supermarket are not much different compared to the convenience store except for the category that usually offers higher discounts. Private labels tend to be more sensitive to discounts, especially in both hypermarket and convenience store (since $\hat{\beta}_{1ijk} + \hat{\beta}_{2ijk} > 0$).

There are no significant direct effects from store format on determining brand discount effectiveness. The store formats tend to moderate few brand factors and category factors including brand discount depth, brand discount breadth, category discount depth and category discount breadth. A deeper discount depth of the brand and category over time in the supermarket can increase an effect of discounts offered. Moreover, while discounts seem to be more effective for brands in categories that generally offer a number of discounts in the hypermarket, the effectiveness are attenuated if these categories usually offer deep discounts. However, there is no evidence of convenience store influencing any effects from these factors.

No moderating effects are observed on brand discount frequency, brand discount variety, competition within the brand's category, or static characteristics of categories which are impulsiveness and storability. Thus, store formats, particularly for the hypermarket and the supermarket, influence the discount effectiveness by the extent of providing appropriate discount activities at the brand level in supermarket and category level in hypermarket. These results address the importance of discount depth and breadth, rather than merely the frequency or variety of offers, in shaping consumer response and enhancing sales effectiveness within these larger store formats.

Table 8: (Second-Stage) Regression of Differential Elasticity and Discount Elasticity on Brand Factors and Category Factors across Store Formats.

Factor	Moderator **Formats**	DV: $\hat{\beta}_{1ijk} + \hat{\beta}_{2ijk}$ Differential Elasticity	DV: $\hat{\beta}_{2ijk}$ Discount Elasticity
Main Effect	(Intercept)	-5362 (2.198)**	0.003 (0.030)
	Hypermarket	1.651 (2.453)	-0.046 (0.040)
	Supermarket	4.659 (2.704)**	-0.049 (0.035)
BDepth	Hypermarket	-0.039 (0.278)	-0.001 (0.005)
	Supermarket	-0.071 (0.358)	0.020 (0.004)***
	Convenience	0.185 (0.463)	0.004 (0.009)
BBreadth	Hypermarket	-0.089 (0.109)	-0.001 (0.001)
	Supermarket	0.016 (0.089)	0.004 (0.002)**
	Convenience	-0.038 (0.136)	-0.003 (0.004)
BFreq	Hypermarket	-0.019 (0.033)	-0.0004 (0.001)
	Supermarket	0.029 (0.039)	-0.0004 (0.001)
	Convenience	-0.022 (0.055)	0.0004 (0.001)
PL	Hypermarket	1.161 (0.431)***	0.019 (0.008)**
	Supermarket	0.627 (0.613)	0.009 (0.007)
	Convenience	2.025 (0.830)**	-0.013 (0.017)
CDepth	Hypermarket	-0.036 (0.257)	-0.014 (0.004)***
	Supermarket	-0.336 (0.315)*	-0.006 (0.004)
	Convenience	-0.035 (0.658)	-0.002 (0.011)
CBreadth	Hypermarket	0.064 (0.064)	0.005 (0.002)***
	Supermarket	-0.017 (0.083)	0.002 (0.001)
	Convenience	0.202 (0.201)	0.0002 (0.003)
CComp	Hypermarket	0.084 (0.099)	0.001 (0.001)
	Supermarket	-0.016 (0.106)	0.003 (0.002)
	Convenience	0.172 (0.116)	-0.001 (0.002)
Impulse	Hypermarket	0.286 (0.462)	-0.003 (0.007)
	Supermarket	-0.175 (0.575)	0.004 (0.007)
	Convenience	0.262 (1.252)	0.012 (0.020)
Storable	Hypermarket	0.507 (0.461)	-0.002 (0.007)
	Supermarket	0.166 (0.502)	0.010 (0.006)
	Convenience	0.416 (0.764)	0.013 (0.013)
Observations		161	161
R-Squared		0.2901	0.6132
Note:			*p<0.1; **p<0.05; ***p<0.01

7 Discussion

Our study investigate the differentiated impacts of regular prices and discounts on brand performance across various categories and store formats within the same retail chain. We specifically addressed two research questions: 1) How do store formats directly influence the differential effectiveness of regular prices and discounts and moderate the impact of brand factors and category factors on these differential effects? and 2) How do store formats directly influence discounts' effectiveness and moderate the impact of brand factors and category factors on the effectiveness of discounts?

To answer these questions, we analyze the performance of 180 brands across 14 frequently purchased categories, which engaged in adjustments of regular prices or the offering of temporary discounts. We obtain brand sales data across format through the loyalty membership database of a Nordic grocery retailer operating under a franchise model with individual store owners. In the following subsections, we discuss our results with respect to the proposed research questions and the implications. In the following subsections, we discuss our results with respect to the proposed research questions as well as broader implications and limitations of our findings.

7.1 Role of Store Formats

The results of our study contribute to the understanding of how different store formats influence the effectiveness of promotional pricing strategies within a multi-format retail setting. Our findings particularly focus on the role of store formats in directly influencing and moderating the impact of brand factors and category factors on the differential effectiveness between regular prices and discounts and the discounts effectiveness.

Firstly, the lack of significant main effects from store formats on discount elasticity contrasts with some prior research (e.g., Haans & Gijsbrechts (2011)), suggesting that discount sensitivity may not be as varied across formats as expected. Haans & Gijsbrechts (2011) highlight that promotional effectiveness tends to decrease as store size increases, particularly noting that larger stores experience diminished sales lifts from discounts compared to smaller stores. This variance could be due to our study's focus on different store formats within the same retail chain, which might not exhibit as pronounced differences in size as those examined by Haans & Gijsbrechts.

However, the findings of store format in affecting discount effectiveness and the differential effects together add complexity to our understanding of consumer behavior. While the type or characteristics of store format may not directly affect how consumers react to discounts, it does influence the differential effects between regular price changes and discounts. This is particularly evident in supermarkets, where we observed a significant differential effect between regular prices and discounts. This effect, which was more pronounced than in other formats, suggests that consumers in supermarkets are responsive to changes in regular prices over discounts. This responsiveness might be enhanced by the smaller size and more curated offerings of supermarkets compared to larger formats like hypermarkets, where the extensive product assortment could dilute the impact of any single discount. This finding may counter some existing assumptions that discounts are universally compelling across all formats. This aligns with our initial discussion in the literature review where we posited that consumer responses to pricing strategies could vary significantly depending on the physical retail environment, echoing theories of store environments. However, it aligns with literature suggesting that different retail environments cater to varying consumer needs, which in turn affects pricing strategy effectiveness (e.g., Jindal et al., 2020).

Our findings indicate a significant sensitivity to temporary discounts changes for private labels within the hypermarket. This effectiveness can be attributed to the extensive product assortment and aggressive pricing strategies that are characteristic of store brands in these large retail environments. In hypermarkets, where consumers are presented with a wide range of options, discounts on private labels can significantly influence purchasing decisions. This suggests that shoppers in hypermarkets are especially responsive to discounts, perhaps because these price reductions make private label products even more attractive compared to their branded counterparts.

We also discovered that store formats moderate certain brand and category factors, including brand discount depth, brand discount breadth, category discount depth, and category discount breadth, with significant implications in hypermarkets and supermarkets. This moderating role suggests that deeper discounts can amplify the effectiveness of promotional strategies within these larger store formats, a finding that supports the literature emphasizing the importance of tailored promotional strategies in different categories in different store environments (e.g., Gauri et al., 2017; Breugelmans et al., 2023). No moderating effects were observed on factors like brand discount frequency or the variety of discounts, which points to a potential saturation in how frequently discounts can influence consumer purchasing behavior across formats. This aspect of the findings suggests that beyond a certain frequency, discounts may cease to have a differential impact, aligning with the notion that too frequent promotions could lead to 'promotion fatigue' among consumers (Srinivasan et al., 2004).

In summary, store formats directly influence the differential effectiveness of regular prices and discounts by making regular price more effective in supermarket. However, only changes of regular prices for private labels offered in hypermarket tend to be more effective compared to the offering temporary discounts. In term of discount effectiveness, store formats do not directly influence the discounts effectiveness but moderate the effects through brand and category factors. There are different moderating effect on brand and categories discount activities.

Grocery retailers can derive practical insights from our findings on the differential impacts of promotional strategies across various store formats. Given the significantly higher sensitivity to regular price adjustments, particularly in supermarkets, retailers should consider emphasizing regular pricing strategies over aggressive discounting for these products, except for private labels in hypermarkets. This approach could prevent consumers from becoming overly conditioned to expect discounts, which might undermine their perception of value and diminish brand loyalty. For supermarkets, where deeper discounts have been shown to enhance promotional effectiveness significantly, retailers could consider designing discount strategies that account for these format-specific responses. Rather than suggesting a shift away from centrally coordinated promotional strategies, our findings highlight that such centralized decisions can benefit from incorporating format-specific differences in consumer responsiveness. However, decisions regarding brand-level discounts should also be aligned with category-level discount activities. A deep brand discount might not be as effective in categories that already exhibit high levels of discounting. The strategy should also ensure that discounting does not become overly frequent to avoid promotion fatigue, which can erode the perceived value of deals over time. Yet, increases in sales volume driven by either reductions in regular prices or discounts do not necessarily translate into increased profitability. Thus, careful consideration of margin impacts and long-term brand value is essential for sustainable financial success.

7.2 Limitations

This study has limitations that suggest opportunities for future research. Firstly, the results are inherently bound by the scope of the data used. Particularly, the grocery retailer data used in our studies predominantly represents loyal customers of a hypermarket, which may not fully capture the potential different shopping behaviors and preferences found in the general population. This suggests caution when generalizing these findings to broader retail contexts or different customer segments. Another significant limitation is the absence of data on additional marketing mix instruments, such as advertising, which are not included in the analysis. This exclusion is particularly relevant as these factors can significantly moderate and influence consumer behavior and purchasing decisions. The lack of this data means that the estimated effects on consumer behavior and sales performance, particularly in the effect of prices might be overestimated (Bijmolt et al., 2005) or not fully representative of the actual market dynamics. Future studies could benefit from incorporating all relevant marketing-mix information and data from a wider range of retail formats, including nontraditional physical stores such as showrooms with different style and installations (Breugelmans et al., 2023). This would enable a more broader and deeper view of consumer behavior across different retail environments and potentially reveal insights into emerging trends and preferences. Another area for future exploration is the operationalization of trip types used as a control variable in our analysis. The classifications of trip types are algorithmically generated based on transaction data, and thus, they serve primarily as proxies for understanding potential shopping patterns and behaviors. This methodological choice allows us to approximate the nature of shopping trips without making direct assumptions about the actual intentions of the shoppers. Consequently, while these trip types provide valuable insights into different shopping patterns, they should be considered conceptual tools rather than definitive indicators of shopper intent. The classifications help control for observed potential relation between shopping trip characteristics and store format, and self-selection bias. Further research could enhance the operationalization of trip types by incorporating direct consumer feedback regarding their shopping intentions, which would allow for a more precise definition of trip types and potentially yield more robust conclusion into how shopping motivations influence responses to pricing strategies and interact across various store formats.

References

Ailawadi, K. L., Harlam, B. A., César, J., & Trounce, D. (2006). Promotion profitability for a retailer: The role of promotion, brand, category, and store characteristics. *Journal of Marketing Research*, *43*(4), 518–535.

Bijmolt, T. H. A., van Heerde, H. J., & Pieters, R. G. M. (2005). New empirical generalizations on the determinants of price elasticity. *Journal of Marketing Research*, *42*(2), 141–156.

Datta, H., van Heerde, H. J., Dekimpe, M. G., & Steenkamp, J.-B. E. M. (2022). Cross-national differences in market response: Line-length, price, and distribution elasticities in 14 Indo-Pacific Rim economies. *Journal of Marketing Research*, *59*(2), 251–270. https://doi.org/10.1177/00222437211058102

Dekimpe, M. G., Gijsbrechts, E., & Gielens, K. (2023). Proximity-store introductions: A new route to big-box retailer success? *Journal of Retailing*, *99*(4), 621–633.

Dhar, S. K., Hoch, S. J., & Kumar, N. (2001). Effective category management depends on the role of the category. *Journal of Retailing*. https://doi.org/10.1016/S0022-4359(01)00045-8

Gauri, D. K., Ratchford, B., Pancras, J., & Talukdar, D. (2017). An empirical analysis of the impact of promotional discounts on store performance. *Journal of Retailing*, *93*(3), 283–303.

Gijsbrechts, E., Campo, K., & Vroegrijk, M. (2018). Save or (over-)spend? The impact of hard-discounter shopping on consumers' grocery outlay. *International Journal of Research in Marketing*, *35*(2), 270–288.

Grewal, D., Breugelmans, E., Gauri, D., & Gielens, K. (2023). Re-imagining the physical store. *Journal of Retailing*, *99*(4), 481–486.

Haans, H., & Gijsbrechts, E. (2011). "One-deal-fits-all?" On category sales promotion effectiveness in smaller versus larger supermarkets. *Journal of Retailing*, *87*(4), 427–443.

Jindal, P., Zhu, T., Chintagunta, P., & Dhar, S. (2020). Marketing-mix response across retail formats: The role of shopping trip types. *Journal of Marketing*, *84*(2), 114–132.

Kamakura, W. A., & Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research*, *26*(4), 379–390.

Koschmann, A., & Isaac, M. S. (2018). Retailer categorization: How store-format price image influences expected prices and consumer choices. *Journal of Retailing*, *94*(4), 364–379.

Krishna, A., Briesch, R., Lehmann, D. R., & Yuan, H. (2002). A meta-analysis of the impact of price presentation on perceived savings. *Journal of Retailing*, *78*(2), 101–118.

Kuntner, T., & Teichert, T. (2016). The scope of price promotion research: An informetric study. *Journal of Business Research*, *69*(8), 2687–2696.

Lu, H., van der Lans, R., Helsen, K., & Gauri, D. K. (2023). DEPART: Decomposing prices using atheoretical regression trees. *International Journal of Research in Marketing*. https://doi.org/10.1016/j.ijresmar.2023.08.009

Narasimhan, C., Neslin, S. A., & Sen, S. K. (1996). Promotional elasticities and category characteristics. *Journal of Marketing*. https://doi.org/10.2307/1251928

Nijs, V. R., Dekimpe, M. G., Steenkamp, J.-B. E. M., & Hanssens, D. M. (2001). The category-demand effects of price promotions. *Marketing Science*. https://doi.org/10.1287/mksc.20.1.1.10197

Pauwels, K., Srinivasan, S., & Franses, P. H. (2007). When do price thresholds matter in retail categories? *Marketing Science*, *26*(1), 83–100.

Raju, J. S. (1992). The effect of price promotions on variability in product category sales. *Marketing Science*. https://doi.org/10.1287/mksc.11.3.207

Scholdra, T. P., Wichmann, J. R. K., Eisenbeiss, M., & Reinartz, W. J. (2022). Households under economic change: How micro- and macroeconomic conditions shape grocery shopping behavior. *Journal of Marketing*, *86*(4), 95–117.

Shankar, V., & Krishnamurthi, L. (1996). Relating price sensitivity to retailer promotional variables and pricing policy: An empirical analysis. *Journal of Retailing*, *72*(3), 249–272.

Srinivasan, S., Pauwels, K., Hanssens, D. M., & Dekimpe, M. G. (2004). Do promotions benefit manufacturers, retailers, or both? *Management Science*, *50*(5), 617–629.

van Heerde, H. J., & Dekimpe, M. G. (2024). Household and retail panel data in retailing research: Time for a renaissance? *Journal of Retailing*. https://doi.org/10.1016/j.jretai.2024.02.004

van Heerde, H. J., & Neslin, S. A. (2017). Sales promotion models. In *International Series in Operations Research and Management Science*.

Widdecke, K. A., Keller, W. I. Y., Gedenk, K., & Deleersnyder, B. (2022). Drivers of the synergy between price cuts and store flyer advertising at supermarkets and discounters. *International Journal of Research in Marketing*. https://doi.org/10.1016/j.ijresmar.2022.10.001

Article 3

The Long-Term Effects of Online Channel Adoption in Grocery Retailing

The Long-Term Effects of Online Channel Adoption in Grocery Retailing

Tanetpong Choungprayoon * Emelie Fröberg † Sara Rosengren ‡

Abstract

This study explores the long-term effects of online channel adoption on grocery retailing. Employing the theory of shopping utility maximization, we investigate purchase behaviors of existing customers in categories with different online shopping utility and link them to changes in purchase patterns (shopping frequency and monetary value) and ultimately retailer revenues. Using five-year customer data from a Nordic grocery retailer, we compare (multichannel) customers who adopt an online channel with customers who do not by using propensity score matching and difference-in-differences analysis. The findings show that multichannel customers had their purchasing habits disrupted and this led them to change in the long run; they buy more products in categories with high perceived online ordering convenience and fewer products in categories with high perceived ordering risk. Although they do not change their purchase frequency, the monetary value (per visit) increases, leading to higher total expenditure and thus long-term revenue to the retailer. Our research contributes to the existing literature, which has focused on the short-term effects of online adoption in the grocery context by empirically showing the long-term effects on the category level, customer level, and retailer level, and by providing a systematic bottom-up framework for the retailer to study the effects of customer adoption over time.

Keywords: Multichannel, Grocery retailing; Online adoption; Customer category purchase; Retailer revenue

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1 Introduction

Demand for online groceries is increasing and even skyrocketed during the Covid-19 pandemic (Roggeveen and Sethuraman 2020), leading established retailers to invest heavily in multichannel offers where the online channel complements the existing offline channel. A key question for such retailers is how the new online channel will impact the purchase behaviors of existing customers and hence their overall revenue to the retailer, especially in the long term.

Previous studies have shown that channel additions are typically beneficial for retailers, as multichannel customers tend to buy more than do single-channel customers (Ansari, Mela, and Neslin 2008; Kumar and Venkatesan 2005; Venkatesan, Kumar, and Ravishanker 2007). However, this effect holds primarily for hedonic rather than functional product categories (Kushwaha and Shankar 2013), when the new channel helps customers overcome barriers of time and place (Melis et al. 2016) and when it provides different benefits from the established one (Bell, Gallino, and Moreno 2018; Biyalogorsky and Naik 2003; Deleersnyder et al. 2002). What is more, the effect depends on channel experience (Melis et al. 2015; R. J.-H. Wang, Malthouse, and Krishnamurthi 2015), meaning that purchase behaviors might change over time. In fact, in durable and apparel retailing, customers have been shown to revert to their regular purchase patterns after three years (Bilgicer et al. 2015).

However, it is unclear how online channel adoption impacts grocery purchase behaviors in the long term. Grocery differs from other retail sectors due to high-frequency purchases of both hedonic and functional products. In addition, customer habits are typically well-established (Melis et al. 2016; R. J.-H. Wang, Malthouse, and Krishnamurthi 2015) and customers tend to purchase a basket of regularly needed goods in stores that carry basically the same categories (e.g., Vroegrijk, Gijsbrechts, and Campo 2013). Research suggests that purchase behaviors of customers who adopt a new channel (thus becoming multichannel customers) depend on the shopping utility offered by that channel (Chintagunta, Chu, and Cebollada 2012; Vroegrijk, Gijsbrechts, and Campo 2013; Campo and Breugelmans 2015; Campo et al. 2020). Shopping utility comprises both acquisition utility (net benefits offered by the channel in terms of the products offered, e.g., price and assortment) and transaction utility (net benefits offered in terms of how easy it is to acquire the product in a specific channel, e.g., ordering and delivery). Multichannel grocery customers have been found to buy more in product categories with high online ordering and delivery convenience and less in product categories with high perceived purchase risk online, compared to offline shoppers (Melis et al. 2015; Melis et al. 2016; Campo et al. 2020; Campo and Breugelmans 2015). This suggests that transaction utility at the category level is a driver of the changed behaviors. Still, this research has not taken a long-term perspective. Thus, it is not clear to what extent existing customers maintain such new purchasing behaviors (Bilgicer et al. 2015; Avery et al. 2012) or how these behaviors affect overall customer purchase patterns (in terms of frequency of visit and monetary value per visit) and ultimately overall revenue for the retailer. In fact, any short-term increases in purchasing behaviors due to new channel adoption could potentially become new habits in the long run, potentially stabilizing or even attenuating short-term effects.

Employing the theory of shopping utility maximization, this study aims to explore whether the purchase behaviors of existing customers change in the long run after they adopt an online channel. We are particularly interested in the overall effect for the retailer in terms of revenues from existing customers. By investigating purchase behaviors in categories that offer different shopping utility in the online channel and linking those behaviors to customer purchase patterns in terms of (average) purchase frequency and monetary value, we contribute to long-term perspective to the literature. More specifically, our proposed conceptual framework links shopping utility (category effects) to changes in customers' shopping frequency and monetary value (customer effects), and ultimately overall revenue from them (retailer effects).

To empirically study the effects of online channel adoption on existing customers in the long term, this research note utilizes real-world data from a large Nordic grocery retailer, focusing on the online and in-store channels of one of their hypermarkets located in a mid-sized town. This empirical material has three main benefits. First, it includes data on actual purchases, both before and after the introduction of the online channel, thus enabling a quasi-experimental design (where we employ several strategies to overcome the endogeneity issues of self-selection). Second, the dataset follows the same customers for over five years, enabling us to explore the long-term effects. Third, the retailer offered the same assortment, prices, and discounts in both channels, thus allowing us to isolate the effects on the perceived transaction utility. We find that customers who adopted an online channel continue to have a higher total expenditure compared to customers who do not. This suggests that there is a long-term value to multichannel investments for grocery retailers, as the retailer gains more revenue from existing customers who adopt an online channel. Our research contributes to the existing literature by providing a conceptual framework linking the long-term effects on the category level, customer level, and retailer level, and providing initial empirical evidence of these effects.

2 Literature Review

Table 1 offers a summary of the literature on channel addition in retailing. Previous research has investigated the impact of channel addition on different levels, ranging from category to customer to retailer. Of the few studies having investigated the temporal effects, none has focused on the long-term effects (defined as more than two years, Bilgicer et al. 2015) in a grocery retail context.

Several studies have found that customers increase their purchases after adopting a new channel, thus finding beneficial effects for the retailer in terms of revenues from existing customers, an increase in customer shopping frequency and monetary value (Ansari, Mela, and Neslin 2008; Li et al. 2015; R. J.-H. Wang, Malthouse, and Krishnamurthi 2015), share of wallet (Campo et al.

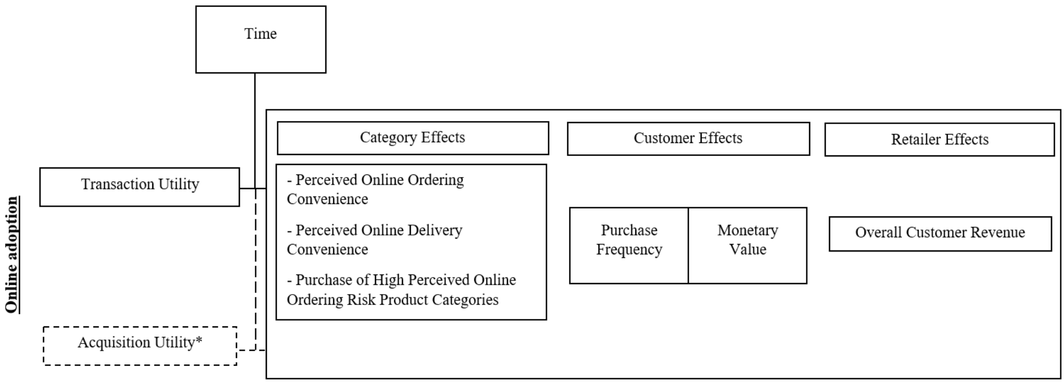
2020; Melis et al. 2016), and profitability (Gensler, Leeflang, and Skiera 2012), In the short run, multichannel customers have higher shopping frequency and monetary value both in the online and offline channels (R. J.-H. Wang, Malthouse, and Krishnamurthi 2015; Campo et al. 2020). They also reallocate their grocery purchase to specific categories (Campo et al. 2020; Campo and Breugelmans 2015). However, Campo and Breugelmans (2015) find that these changes are attenuated by online experience. This means that the shopping utility for multichannel customers may change over time. Still, as previous research has only investigated customer responses in the short term, it is not clear what effects this will have on the overall revenue in the long term. The current study contributes to this literature by focusing on grocery and linking category, customer, and retailer effects in the long term.

Table 1: Overview of Previous Research on the Effects of Channel Addition

Study	**Unit of Analysis**	**Study of Temporal Effects**	**Temporal Term of Effects**	**Context of the Study**	**Dependent Variables**	**Empirical Findings**
Ansari, Mela, and Neslin (2008)	Customer	No	–	Consumer durable and apparel	Shopping frequency, monetary value	Customers migrate to the Internet channel and multichannel users have higher shopping frequency and monetary value
van Nierop et al. (2011)	Customer	No	–	Fashion, sports, living, children's	Shopping frequency, monetary value	Introduction of informational website decreases the customers' shopping frequency and monetary value
Gensler, Leeflang, and Skiera (2012)	Customer, Retailer	No	–	Banking	Revenue, profitability	Adoption of online channel increases revenue and profitability
Avery et al. (2012)	Retailer	Yes	Long-Term	Consumer durable and apparel	Revenue, total customer counts	Introduction of offline store decreases retailers' revenue in the direct channel in the short term but increases their revenue in the long term
Li et al. (2015)	Customer	Yes	Short-Term	Natural health	Shopping frequency, purchasing volume	Late majority and innovators do not purchase more after adopting a new channel; light shoppers do
Bilgicer, Jedidi, Lehmann, and Neslin (2015)	Retailer	Yes	Long-Term	Consumer durable and apparel	Revenues from existing customers	Retailers get more revenues from multichannel customers initially; then the revenues drop as customers return to their regular spending pattern over time
Wang, Malthouse, and Krishnamurthi (2015)	Customer	No	–	Grocery	Shopping frequency, monetary value	Customers increase their shopping frequency and monetary value after adopting a mobile service channel
Melis et al. (2016)	Category, Customer	No	–	Grocery	Share of wallet	Multichannel shoppers have a higher share of wallet at the chain where they started buying online
Campo et al. (2020)	Category, Customer	No	–	Grocery	Share of wallet	Categories that are heavy/bulky and/or can be planned ahead benefit from the online channel. Categories that are sensory and can be planned ahead moderate the effect of price and assortment.
Current study	Category, Customer, Retailer	Yes	Long-term	Grocery	Category purchases, customers' shopping frequency and monetary value, revenues to the retailer	Customers who adopted an online channel had their purchasing habits disrupted and this led them to change in the long term; they buy more product categories with high perceived online ordering convenience and fewer products in categories with high perceived ordering risk. Although existing customers do not change their purchase frequency, the monetary value per visit increases, leading to higher total expenditure and thus long-term revenue to the retailer.

3 Conceptual Framework

In this section, we provide a conceptual framework regarding how customers' online adoption affects their purchase patterns over time and we derive the three research questions that guide our investigation. The framework relies on the theory of shopping utility maximization to explain how customers respond to an online channel. We elaborate on the potential long-term outcomes on existing customers' purchasing habits in specific categories and their revenues to the retailer, which combines customer shopping frequency and monetary value, in the long run (Figure 1).



*The grocery retailer has no difference in price and assortment across channels and thus acquisition utility is constant in our data.

Figure 1: Conceptual Framework

Shopping Utility Maximization

Previous studies on multichannel and multistore purchase behaviors have used shopping utility to explain how customers allocate decisions across those behaviors (Vroegrijk, Gijsbrechts, and Campo 2013; Campo et al. 2020). The theory of shopping utility maximization suggests that when deciding how to purchase groceries across channels, customers can be expected to select a purchase pattern that provides the most overall shopping utility. Purchasing groceries involves the allocation of both money and other scarce recourses such as time and effort. Thus, both monetary and nonmonetary benefits and costs must be considered. Shopping utility can therefore be divided into (a) acquisition utility and (b) transaction utility (Campo et al. 2020), where acquisition utility refers to the net benefits offered by the channel in terms of the product offered (e.g., price, assortment) and transaction utility refers to net benefits offered in terms of how easy it is to acquire the product in a specific channel (e.g., delivery, ordering). Consequently, customers can be expected to decide on the channel in a way that maximizes their total utility, comprising a combination of acquisition and transaction utility.

Shopping utility theory can be used by a retailer to understand what changes will occur for existing customers who adopt the online channel. When the grocery retailer has no difference in price and assortment across channels, acquisition utility is constant and thus the transaction utility for online purchasing will determine the utility of the online channel. Transaction utility varies across different product categories. Previous studies (Campo et al. 2020; Campo and Breugelmans 2015; Melis et al. 2016) show that the online channel enhances transaction utility by offering convenience (time and effort), which in turn leads customers to buy more bulky or heavy product categories (i.e., categories with high perceived ordering convenience) and planned product categories (i.e., categories with high perceived delivery convenience). On the other hand, the online channel also decreases transaction utility in product categories that require physical inspection (i.e., categories with high perceived online purchase risk), leading customers to buy less sensory products online.

Hence, in the short term, we expect to see positive effects on customers' shopping monetary value from high perceived ordering convenience and high delivery convenience product categories and negative effects on existing customers' monetary value from high perceived online purchase risk products (Campo et al. 2020; Campo and Breugelmans 2015; Melis et al. 2016). However, the effects on the shopping frequency and the subsequent revenues to the retailer remain unclear. For example, customers may purchase more high perceived delivery convenience products online while still maintaining their regular purchase of this category offline, and vice versa.

Long-Term Effects on Customer Purchase Behavior and Retailer Revenue

Although the short-term effects of shopping utility maximization have been documented in the literature, the long-term effects on existing customers' shopping behaviors and their total revenue for the retailer are unclear. Online buying experience in grocery shopping can attenuate the category-specific effects caused by online transaction utility (Campo and Breugelmans 2015), meaning that multichannel customers may no longer obtain net (dis)utility from purchasing certain product categories over time. Empirically, Campo and Breugelmans (2015) found that customers purchased a larger share of categories with high perceived online ordering risk and a smaller share of categories with high perceived online delivering convenience as they gained more online buying experience. However, the short-term category-specific effects could also be reinforced over time. This would be due to the net (dis)utility from purchasing specific categories that could (dis)incentivize customers to perform these behaviors repeatedly and turn them into new habits (Shah, Kumar, and Kim 2014).

Theoretically, it is unclear how the attenuating mechanism from aggregate online experience or the reinforcing mechanism from habit formation will impact long-term purchase behaviors. Moreover, the long-term effects for the retailer in terms of revenue will depend on the purchasing patterns developed by the customers in terms of their purchase frequency and the monetary value (per visit) increases. For example, customers who adopted an online channel may maintain their higher level of purchases in categories with high online ordering and high delivery convenience because they enjoy this rewarding behavior, while also increasing their purchases in categories with high online ordering risk due to more experience of obtaining the products over time. As a result, these customers may have higher monetary value but may visit both online and offline channels less, as most of purchases are already made online; hence their total revenues for the retailer remain unchanged. This means that the effects on customers' frequency and monetary value after adopting an online channel over time remain to be explored. Thus, we ask the following research questions about online channel adoption from existing grocery customers:

RQ1: What are the long-term category effects of online channel adoption?

RQ2: What are the long-term customer effects of online channel adoption?

RQ3: What are the long-term retailer effects of online channel adoption?

4 Methodology

In this section, we first describe our data and the empirical setting. Next, we provide initial evidence of the effects of online adoption based on a difference-in-differences (DID) analysis. Accounting for the potential biases from customer self-selection and customer heterogeneity, we employ propensity score matching and estimate DID to investigate the long-term effects on category levels across existing customers, their overall shopping frequency and monetary value, and their revenues to the retailer, respectively.

4.1 Data Description

To evaluate the long-term effects of online adoption, we use real-world data from a Nordic grocery retailer. We use point of sales data from loyalty cards from customers at one specific hypermarket in a mid-sized city. The retailer introduced an online channel in October 2015. At this point, the retailer was the only online grocery offer available in the local market, but in subsequent years several competing options were launched. The hypermarket offers a full range of grocery products both offline and online. Prices and discounts are the same in both channels.

Data come from two different datasets (Oct 2014–Nov 2016 and Aug 2017–July 2019) [1]. We focus on customers that are available in both datasets. As our focus is on channel adoption of existing customers, customers must have made at least 10 purchases before the introduction of the online channel and adoption, and must adopt the online channel within 7 weeks of the introduction to be included in the analysis. In total, we track 578 households (147 of which adopt the online channel) and 116,982 receipts with 1,749,812 products. The retailer charged a picking and delivery fee for the online channel, but this fee is not included in the analyses.

We include a total 358 product categories of which 205 are coded according to perceived online (a) ordering convenience, (b) delivery convenience, and (c) ordering risk.

Table 2 summarizes the measures and definition of variables in this study. All operationalizations are aligned with previous studies. Perceived online ordering convenience, perceived online

[1] We have access to all online/multichannel customers as well as a random sample of 25% of all offline customers.

delivery convenience, and perceived online ordering risk are conceptualized at the category level based on Campo et al. (2021). More specifically, we operationalize this as planning product categories, heavy/bulky product categories, and sensory product categories, respectively.

Table 2: Variables of Interest, Measures, and Definitions

Variables of Interest	**Measures**	**Definition**
Specific Category Purchases		
Perceived online ordering convenience	Planning	Money spent on categories with high perceived online ordering convenience. This includes 205 grocery categories with ratings above 3.5 on a 7-point planned purchase Likert scale (1 = not planned, 7 = usually planned) based on Campo et al. (2021) (local currency).
Perceived online delivery convenience	Heavy/bulky	Money spent on categories with high perceived online delivery convenience. This includes 205 grocery categories with ratings above 3.5 on a 7-point heavy/bulky Likert scale (1 = not heavy/bulky, 7 = very heavy/bulky) based on Campo et al. (2021) (local currency).
Perceived online ordering risk	Sensory	Money spent on categories with high perceived online ordering risk. This includes 205 grocery categories with ratings above 3.5 on a 7-point sensory Likert scale (1 = not sensory, 7 = very sensory) based on Campo et al. (2021) (local currency).
Overall Shopping Behaviors		
Frequency	Frequency	Average number of purchase incidences per week (times).
Monetary value	Monetary	Average amount of money spent per purchase incidence (local currency).
Total Customer Revenues		
Total expenditures	Expenditure	Total amount of money spent by customers over a given period (local currency).
Period of Time		
Before adopting an online channel	Pre	52 weeks prior to the first online purchase of the treated household.
After adopting an online channel (short term)	Short	0–52 weeks following the first online purchase.
Over 2 years after adopting an online channel	Long	146–198 weeks following online introduction.

4.2 Model-Free Evidence

To provide initial evidence of the effects of online adoption, we first implemented a simple DID analysis comparing customers who adopted an online channel (Multichannel) and those who did not (Offline). In Table 3, the DID columns represent the isolated difference compared to the average pre-period and online adoption effects (see Figure A1 in Appendix for parallel trend assumption). We assessed the first difference in category purchases, customers' shopping frequency and monetary value, and their total revenues to the retailer for the year prior to their online channel adoption (*Pre*), and relative differences in performance up to four years after the adoption (short-term (*Short*), and long-term (*Long*), respectively). This model-free evidence shows that the existing customers who adopt the online channel significantly change their category purchase patterns as well as their overall frequency and monetary value in the long run, leading to higher revenue for the retailer. However, the model-free results do not account for the self-selection bias of those existing customers who decide to adopt an online channel (i.e., multichannel shoppers are likely to shop significantly more than offline shoppers, which shows that customers with a higher shopping frequency and monetary value are likely to adopt an online channel (Boehm 2008; Konuş, Verhoef, and Neslin 2008; Kumar and Venkatesan 2005). Hence, it is difficult to conclude whether this long-term change is due to the online adoption or to self-selection bias.

Table 3: Model-Free Evidence of the Effects of Online Channel Adoption

		Pre	Short	DID	Long	DID
Planning	Multichannel	1627	1480	-366	1441	381
	Offline	1242	1462			675
Heavy/Bulky	Multichannel	29	53	0	48	23
	Offline	29	53			26
Sensory	Multichannel	388	445	25	113	-136
	Offline	201	233			62
Frequency	Multichannel	1.19	1.23	0.07	1.16	0.09
	Offline	0.93	0.90			0.80
Monetary Value	Multichannel	622	661	49	706	83
	Offline	339	329			340
Expenditure	Multichannel	32440	36526	4873	35263	4193
	Offline	15935	15147			14565

4.3 Propensity Score Matching

Since customers self-select to the online channel, it may be that customers who adopt the online channel are genuinely different from those who do not, regardless of online channel adoption. To deal with this issue, we employ propensity score matching, allowing us to match multichannel customers with offline customers who are similar to them prior to channel adoption. We argue that any differences between customers adopting online channel and those who do not should be reflected in pre-introduction purchasing behaviors, captured by frequency and monetary value, but also include the distance to the offline store in our matching. Modeling the ith customer's online adoption in period t as the dependent variable, we estimate propensity scores using the following regression model:

$$\text{Treat}_{i,post} = \alpha_0 + \alpha_1\text{Frequency}_{i,pre} + \alpha_2\text{MonetaryValue}_{i,pre} + \alpha_3\text{Distant}_{i,pre} + \varepsilon_i \tag{1}$$

where post is a period of seven weeks after the introduction of the online channel, pre is one year prior to the introduction of the online channel, and Distant is a dummy variable that takes the value 1 if the customer's registered postal code is more than three kilometers from the physical store.

Upon matching, our samples are more balanced (see Appendix A1 for summary statistics before and after matching). We further explore additional characteristic that could be influenced by channel adoption, namely the number of units purchased (*Volume*), deal proneness represented by the ratio of products purchased on deals to total purchase volume (*Deal*), and the family situation reflected in total number of purchased diapers (*Family*) (Kumar and Venkatesan 2005; Venkatesan, Kumar, and Ravishanker 2007; Chu, Chintagunta, and Cebollada 2008; Chu et al. 2010; Kushwaha and Shankar 2013). As there is still some variation in terms of *Volume*, *Deal*, and *Family* between matched pair i in the matching period, we include these variables as controls in our DID Analysis.

4.4 DID Analysis

We calculate a difference in all our dependent variables between the matched pairs. We then test the following regression equation,

$$Y_{i,t} = \beta_1\text{Short}_{i,t} + \beta_2\text{Long}_{i,t} + \beta_3\text{Volume}_{i,t} + \beta_4\text{Deal}_{i,t} + \beta_5\text{Family}_{i,t} + \xi_i + \varepsilon_i \tag{2}$$

where $Y_{i,t}$ is the difference between the *Multichannel* and *Offline* matched pair i in period t of the customers' purchase behaviors (*Planning*, *Heavy/Bulky*, *Sensory*, *Frequency*, *Monetary Value*, and *Expenditures*). Consistent with the model-free evidence, purchase behaviors in the year prior to online channel adoption, and relative differences in category purchases, customers' shopping frequency and monetary value, and their total revenues to the retailer up to four years after the adoption are investigated. Period t includes the period before the first purchase (*Pre*), the short-term (*Short*), and the long-term (*Long*). *Short* and *Long* are dummy variables.

As we are interested in long-term effects, we focus on the β_2 coefficient (pre is a baseline situation when β_1 and β_2 are equal to zero). We use a fixed effect model to account for unobserved heterogeneity. Thus, our model tests the pairwise difference between customers who adopted the online channel and customers who did not, and the difference between the period prior to adoption and the long-term period following adoption. Given that we take a full year into account, we do not control for seasonal effects.

5 Results

Table 4 shows the results of our DID analysis of pair-wise matches between *Multichannel* and *Offline* customers. In the Appendix (Figure A2), we illustrate that the parallel trend assumption holds.

At the category level, the results indicate that the short-term effects from changes in transaction utility found in previous research are both attenuated by online buying experience and reinforced by habit formation in the long run. First, there is no difference between the purchases of products with high perceived online ordering convenience (*Planning*) in the long-term period and the period prior to adoption, between the multichannel and the offline customers, 95% CI [-681, 694.1]. Second, purchases of products with high perceived online delivery convenience (*Heavy/Bulky*) are higher in the long-term period, 95% CI [104.4, 572.19]. This category purchases are higher both online and offline for the multichannel customers, indicating that they enjoy purchasing not only from the online channel that provides a direct increase in shopping utility, but also from the offline channel. Surprisingly, the purchases of products with high perceived online ordering risk (*Sensory*) remain lower in the long-term period, 95% CI [-788.84, 188.09]. This suggests a reinforcing effect in which multichannel customers become used to purchasing less in this category over time. Answering RQ1, we thus find that, in the long term, existing customers who adopted the online channel purchase more in product categories with high perceived online delivery convenience, but less in product categories with high ordering risk.

At the customer level, the results show that multichannel customers make fewer frequent purchases (*Frequency*), 95% CI [-0.22, 0], but in the long term spend a higher monetary value per purchase occasion (*Monetary Value*), 95% CI [54.71, 152.41], compared to before adoption. Although this reflects a reversion in customers' shopping patterns in terms of frequency (i.e., they visit the same number of times regardless of the channel), they buy more, especially from high perceived online delivery convenience categories. Answering RQ2, this suggests a stable purchase pattern in terms of frequency, but a higher monetary value for existing customers in the long term.

At the retailer level, the results suggest that multichannel customers have higher total expenditures (*Expenditure*) in the long-term period compared to the period prior to adoption, 95% CI [-356.05, 1488.53]. Answering RQ3, this implies a higher total revenue from existing customers adopting the online channel for the grocery retailer in the long term. This increase in revenues is due to the long-term increase in overall monetary value of multichannel customers after adopting an online channel, driven by categories with high perceived online ordering convenience.

Table 4: Fixed Effect Panel Regression Results of the DID Analysis of Pair-Wise Matches between Multichannel and Offline Customers

	Category Effects			**Customer Effects**		**Retailer Effects**
	Planning	Heavy/Bulky	Sensory	Frequency	Monetary	Expenditure
Panel A: Multichannel Customer Purchases (Total)						
Short	1114.53 (337.15)	247.33 (114.69)	570.62 (239.52)	-0.08 (0.05)	45.63 (23.96)	643.20 (452.25)
Long	6.55 (343.77)	338.29 (116.95)	-300.38 (244.23)	-0.11 (0.06)	103.56 (24.43)	566.24 (461.15)
R-squared	0.88	0.73	0.69	0.41	0.23	0.93
Panel B: Multichannel Customer Purchases (Online Channel)						
Short	1156.47 (359.30)	624.51 (122.11)	-71.11 (231.30)	-0.33 (0.07)	431.73 (57.71)	703.20 (438.89)
Long	695.39 (347.54)	287.13 (118.11)	245.72 (223.73)	-0.35 (0.06)	307.47 (55.82)	-1842.49 (424.53)
R-squared	0.93	0.80	0.88	0.69	0.23	0.97
Panel C: Multichannel Customer Purchases (Offline Channel)						
Short	-197.23 (312.31)	244.98 (112.28)	-138.20 (225.56)	0.03 (0.05)	-24.38 (23.85)	363.39 (474.01)
Long	-650.46 (309.30)	129.50 (111.20)	-309.66 (223.39)	-0.02 (0.05)	25.61 (23.62)	119.43 (469.43)
R-squared	0.87	0.66	0.69	0.45	0.15	0.92

Notes: Standard errors in parentheses; includes covariates specified in Eq. 2.

6 Discussion

This investigation sets out to provide retailers with a better understanding of how online channel adoption impacts the purchase behaviors of existing customers and hence their overall revenue, especially in the long term. Our results show that customers who adopt an online channel had their purchasing habits disrupted, but also that their habits changed in the long term. We find that existing customers who adopt an online channel continue to purchase more categories with high perceived delivery convenience while avoiding categories with high perceived ordering risk over time. However, they do not appear to purchase more products of high ordering convenience—that is, their purchases do not become more planned—in the long term. Moreover, existing customers who adopt an online channel purchase more (per visit), while their frequency of visits remains the same. Thus, the purchase habits are stable in terms of frequency and the category effects mainly influence the monetary value. This is in line with the insignificant effect on ordering convenience in which customers do not make more planned purchases in the long term. Overall, these changes lead to higher total expenditure and thus to more revenues for the retailer.

Our findings contribute to previous research by showing the persistent, long-term effects on various aspects of customer purchasing habits. However, it should be noted that our empirical results hint an attenuating effect of online adoption over time—the magnitudes of the effects are smaller in the long term compared to the short term. In the short term, the results are consistent with the existing literature, in which an online channel increases transaction utility for online purchases, inducing customers to buy more products with high online ordering convenience and high delivery convenience from an online channel (Campo et al. 2020; Campo and Breugelmans 2015) and leading customers to spend more (higher monetary value) and buy more often (frequency; Wang, Malthouse, and Krishnamurthi 2015). However, contrary to these studies, we also found that customers purchase more product categories with high online ordering risk, although this positive effect decreases over time. One possibility is that the customers who adopt the online channel early are less risk-averse overall. To explore this, we re-ran the analysis on customers that adopted the online channel three years after the channel was introduced and found that these adopters indeed purchased fewer products with high perceived risk upon adopting the online channel (see more in Appendix Table A2). These results suggest that retailers must be careful when interpreting short-term purchase behaviors of early adopters, as they are less likely to indicate what other customer groups will do, especially in the long term.

The proposed framework links shopping utility (category level), to changes in purchase patterns in terms of shopping frequency and monetary value (customer level), and ultimately overall revenue (retailer level). This framework can be used by retailers to better understand the bottom-up effect of offering a new channel starting with utility at the category level. By using this framework when analyzing point of sales data from loyalty cards, retailers can follow changes in customer behavior at all three levels across each channel as well as in total. For our grocery retailer, the transaction utility offered by the new online channel had a positive impact on the purchase behaviors of existing customers and hence their overall long-term revenue to the retailer. For other retailers, the relationship could differ. This is especially true for retailers that use different pricing and assortments across channels. For such retailers, our framework can be extended to also study acquisition utility.

Overall, our results present initial evidence of the benefits to retailers of offering several channels to existing customers in grocery retail, although they remain limited by the specific strategies of the retailer in our study. Future research is needed to investigate the generalizability of our findings. Such research should also explore how acquisition utility impacts the purchase behaviors of existing customers in the long term. Similarly, the framework could be used to provide more in-depth insights into channel adoption in other retail categories, which to date has mainly focused on customer-level effects (Avery et al. 2012; Bilgicer, Jedidi, Lehmann, and Neslin 2015). It is our hope that this study will help spur additional research on this managerially relevant topic.

References

Ansari, Asim, Carl F. Mela, and Scott A. Neslin (2008). "Customer Channel Migration." *Journal of Marketing Research*, 45 (1), 60–75.

Avery, Jill, Thomas J. Steenburgh, John Deighton, and Mary Caravella (2012). "Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities over Time." *Journal of Marketing*, 76 (3), 96–111.

Bell, David R., Santiago Gallino, and Antonio Moreno (2018). "Offline Showrooms in Omnichannel Retail: Demand and Operational Benefits." *Management Science*, 64 (4), 1629–1651.

Bilgicer, Tolga, Kamel Jedidi, Donald R. Lehmann, and Scott A. Neslin (2015). "The Long-Term Effect of Multichannel Usage on Sales." *Customer Needs and Solutions*, 2 (1), 41–56.

Biyalogorsky, Eyal and Prasad Naik (2003). "Clicks and Mortar: The Effect of On-Line Activities on Off-Line Sales." *Marketing Letters*, 14 (1), 21–32.

Boehm, Martin (2008). "Determining the Impact of Internet Channel Use on a Customer's Lifetime." *Journal of Interactive Marketing*, 22 (3), 2–22.

Campo, Katia and Els Breugelmans (2015). "Buying Groceries in Brick and Click Stores: Category Allocation Decisions and the Moderating Effect of Online Buying Experience." *Journal of Interactive Marketing*, 31, 63–78.

Campo, Katia, Lien Lamey, Els Breugelmans, and Kristina Melis (2020). "Going Online for Groceries: Drivers of Category-Level Share of Wallet Expansion." *Journal of Retailing*.

Chintagunta, Pradeep K., Junhong Chu, and Javier Cebollada (2012). "Quantifying Transaction Costs in Online/Offline Grocery Channel Choice." *Marketing Science*, 31 (1), 96–114.

Chu, Junhong, Marta Arce-Urriza, Jose-Javier Cebollada-Calvo, and Pradeep K. Chintagunta (2010). "An Empirical Analysis of Shopping Behavior Across Online and Offline Channels for Grocery Products." *Journal of Interactive Marketing*, 24 (4), 251–268.

Chu, Junhong, Pradeep Chintagunta, and Javier Cebollada (2008). "A Comparison of Within-Household Price Sensitivity Across Online and Offline Channels." *Marketing Science*, 27 (2), 283–299.

Deleersnyder, Barbara, Inge Geyskens, Katrijn Gielens, and Marnik G. Dekimpe (2002). "How Cannibalistic Is the Internet Channel?" *International Journal of Research in Marketing*.

Gensler, Sonja, Peter Leeflang, and Bernd Skiera (2012). "Impact of Online Channel Use on Customer Revenues and Costs to Serve." *International Journal of Research in Marketing*, 29 (2), 192–201.

Konus, Umut, Peter C. Verhoef, and Scott A. Neslin (2008). "Multichannel Shopper Segments and Their Covariates." *Journal of Retailing*, 84 (4), 398–413.

Kumar, V. and Rajkumar Venkatesan (2005). "Who Are the Multichannel Shoppers and How Do They Perform?" *Journal of Interactive Marketing*, 19 (2), 44–62.

Kushwaha, Tarun and Venkatesh Shankar (2013). "Are Multichannel Customers Really More Valuable?" *Journal of Marketing*, 77 (4), 67–85.

Li, Jing, Umut Konus, Koen Pauwels, and Fred Langerak (2015). "The Hare and the Tortoise: Do

Earlier Adopters of Online Channels Purchase More?" *Journal of Retailing*, 91 (2), 289–308.

Melis, Kristina, Katia Campo, Els Breugelmans, and Lien Lamey (2015). "The Impact of the Multi-Channel Retail Mix on Online Store Choice." *Journal of Retailing*, 91 (2), 272–288.

Melis, Kristina, Katia Campo, Els Breugelmans, and Lien Lamey (2016). "A Bigger Slice of the Multichannel Grocery Pie." *Journal of Retailing*, 92 (3), 268–286.

Roggeveen, Anne L. and Raj Sethuraman (2020). "How the COVID-19 Pandemic May Change the World of Retailing." *Journal of Retailing*, 96 (2), 169.

Shah, Denish, V. Kumar, and Kihyun Hannah Kim (2014). "Managing Customer Profits: The Power of Habits." *Journal of Marketing Research*, 51 (6), 726–741.

Venkatesan, Rajkumar, V. Kumar, and Nalini Ravishanker (2007). "Multichannel Shopping: Causes and Consequences." *Journal of Marketing*, 71 (2), 114–132.

Vroegrijk, Mark, Els Gijsbrechts, and Katia Campo (2013). "Close Encounter with the Hard Discounter." *Journal of Marketing Research*, 50 (5), 606–626.

Wang, Kitty and Avi Goldfarb (2017). "Can Offline Stores Drive Online Sales?" *Journal of Marketing Research*, 54 (5), 706–719.

Wang, Rebecca Jen-Hui, Edward C. Malthouse, and Lakshman Krishnamurthi (2015). "On the Go: How Mobile Shopping Affects Customer Purchase Behavior." *Journal of Retailing*, 91 (2), 217–234.

Appendix

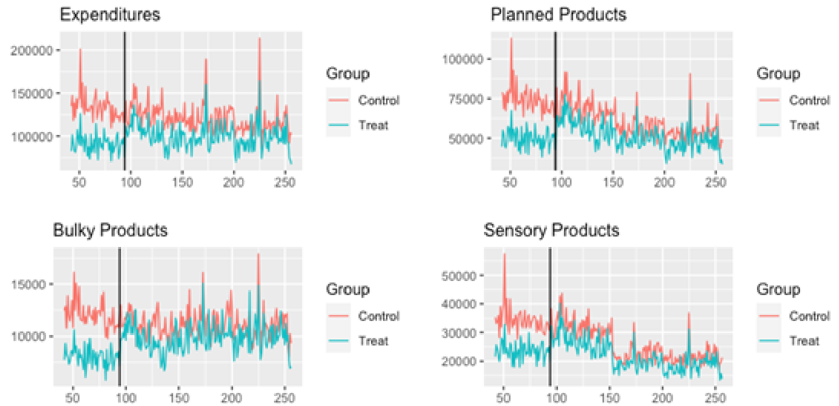


Figure A1: Purchasing behaviors over time of the treatment group, which represents customers who adopted an online channel (Multichannel), and control group, which represents customers who never adopted an online channel (Offline) without adjusting for self-selection bias

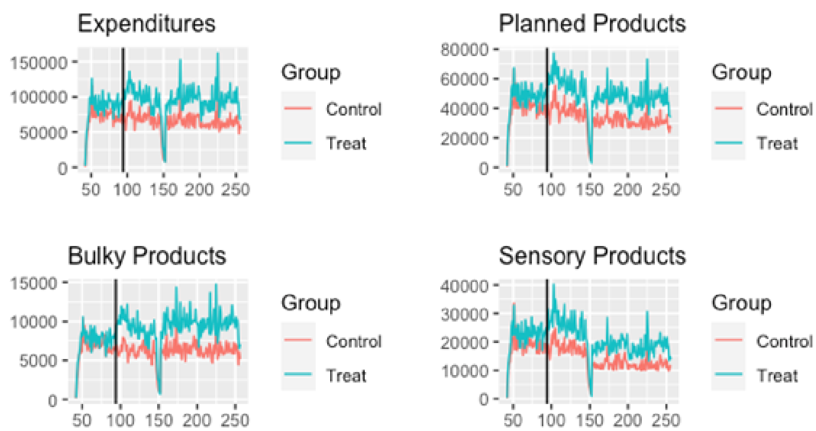


Figure A2: Purchasing behaviors over time of the treatment group, which represents customers who adopted an online channel (Multichannel), and control group, which represents customers who never adopted an online channel (Offline) after adjusting for self-selection bias

Table A1: Summary Statistics for All Samples and Comparison Before and After Matching

	Multichannel	**Offline (Matched)**	**Offline (Unmatched)**	**All Customers**
Frequency	1.20 (1.12)	1.18 (0.89)	0.93 (0.75)	0.69 (0.77)
Monetary	609 (278)	520.91 (254)	339.64 (218)	369.72 (268)
Distant	0.23 (0.42)	0.23 (0.42)	0.45 (0.50)	0.40 (0.49)
Volume	1494 (1013)	1301.47 (749)	799.68 (688)	661.13 (768)
Deals (% of volume)	0.37 (0.39)	0.43 (0.45)	0.56 (0.60)	1.61 (5.46)
Family	8.93 (13.90)	2.32 (8.02)	1.26 (5.61)	1.99 (6.83)
N	146	146	431	4674

Notes: M (SD)

Table A2: Fixed Effect Analysis of Late Adopters

	Planning	Bulky	Sensory	Frequency	Monetary	Total Expenditures
Panel A: Multichannel Customer Purchases (Total)						
Short	361.23 (388.03)	316.18 (142.49)	-275.10 (211.01)	-0.02 (0.07)	96.31 (21.58)	689.59 (532.89)
R-squared	0.95	0.78	0.93	0.76	0.19	0.97
Panel B: Multichannel Customer Purchases (Online Channel)						
Short	782.34 (547.58)	169.56 (179.46)	533.21 (301.25)	0.00 (0.10)	383.60 (58.70)	-972.98 (719.42)
R-squared	0.96	0.86	0.94	0.84	0.39	0.98
Panel C: Multichannel Customer Purchases (Offline Channel)						
Short	141.40 (371.49)	195.05 (131.72)	-78.98 (218.35)	0.09 (0.07)	20.12 (21.24)	412.76 (511.04)
R-squared	0.95	0.81	0.93	0.77	0.03	0.97

Notes: In this analysis, August 1, 2018 is used as the late treatment date. Propensity score matching is performed on the 52 weeks prior to that date. Customers are allowed to adopt the online channel within ±4 weeks of the late treatment date, resulting in 95 matched pairs of adopters and control customers. The analysis compares 48 weeks before (pre) and 48 weeks after (short). The model specification follows the main analysis, but long-term effects are not available.

Article 4

How Did COVID-19 Affect Playlist Followers on Spotify?

How did COVID-19 Affect Playlist Followers on Spotify? *

Tanetpong Choungprayoon † Max J. Pachali ‡ Hannes Datta §

Abstract

The COVID-19 pandemic disrupted traditional music consumption and accelerated the shift toward streaming platforms. While global subscriptions grew, less is known about how engagement changed within platforms. This study examines weekly changes in Spotify playlist followers from October 2019 to October 2020 to assess shifts in user behavior and stakeholder visibility. We estimate a unit-fixed effects model using three measures of pandemic impact: the official declaration date, a government stringency index, and residential mobility data. We find no significant change in average follower growth after the pandemic declaration, but growth increased when users spent more time at home. Playlists with moderate or small existing followings experienced stronger growth than top-tier (i.e., most popular) playlists, suggesting engagement expanded across a wider range of content. Spotify-curated playlists were more resilient and productive than those curated by major labels or independent entities, even after accounting for platform-driven promotion. While playlists with a higher share of major label content saw some growth, track-level popularity had a stronger effect. These findings highlight how behavioral shifts affected existing music content consumption patterns and stakeholders' visibility within the streaming platforms.

Keywords: Playlist Followers; Lockdown Restrictions; Music Streaming; Pandemic; Playlist Featuring

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1 Introduction

After the outbreak of the COVID-19 pandemic, the music industry, along with many creative industries suffered from government interventions and restrictions on live performance and in-person gatherings (WIPO, 2022). These restrictions, along with reduced commuting and social activities, contributed to a decline in music consumption and streaming activity, particularly during the first months following the outbreak in early 2020 (Denk et al., 2022; Sim et al., 2022). As a result, revenues from both live concerts and physical and digital record sales dropped significantly, at least 18% in the US and 5% globally (RIAA, 2021; IFPI, 2021). In contrast, music streaming platforms reported growth in both user numbers and subscription revenues during and after the pandemic at least 13% in the US and 18% globally (RIAA, 2021; IFPI, 2021). This contradiction suggests that the entry of new users might affect how existing music content was consumed and how stakeholders within the platform gained visibility and influence, especially from the perspective of audience behavior and engagement.

As the pandemic pushed audiences away from traditional formats more toward digital platforms, streaming services became the primary channel for music discovery and consumption. These platforms generally provide users with on-demand access to extensive music catalogs and support user engagement through features like algorithmic recommendations and curated playlists. These curated playlists are important in shaping how listeners discover and engage with music, as they introduce users to a wider variety of tracks and facilitate music exploration (Datta et al., 2018). Moreover, their follower counts are highly correlated with actual active listeners (Datta & Pachali, 2024). Since playlists are both discovery tools and exposure channels, changes in their follower numbers offer insight into how users' behavior evolved during the pandemic and how that behavior may have affected the visibility and positioning of different stakeholders within the platform.

The music streaming ecosystem is composed of stakeholders with vastly different levels of influence and resources, from global platforms and major record labels to independent curators and artists. Given their varying resources and market power, stakeholders' abilities to counteract the adverse effects of the pandemic or capitalize on new opportunities likely varied. For instance, playlists curated by streaming platforms might have been able to leverage algorithmic promotion and user data to retain followers, while major label-backed playlists could have gained traction as traditional promotion channels became more limited. Independent curators, however, may have faced greater challenges in maintaining visibility and engagement. Building on this, our research investigates the changes in playlist followers, an observable proxy for sustained user engagement on the platform, across different curators before and after the pandemic declaration. We are particularly interested in understanding whether certain types of playlists were more resilient than others in maintaining or even gaining followers during the pandemic. Thus, we examine how playlist follower changes varied not only across curators but also across different levels of playlist popularity and content composition, as these characteristics are likely to moderate the extent to which playlists retained or gained followers during the pandemic. Accordingly, we pose the following empirical research questions:

RQ 1: How did the number of followers for playlists change during the pandemic?

RQ 2: How did follower dynamics differ across playlists with varying levels of popularity during the pandemic?

RQ 3: How did playlists curated by music streaming platforms, major labels, and independent curators differ in their resilience to changes in follower numbers during the pandemic?

RQ 4: Did playlists featuring a higher proportion of tracks from major labels experience greater follower growth during the pandemic?

These research questions aim to uncover shifts in user engagement patterns via playlists following and competitive positioning within the music streaming platform during the pandemic. By examining overall changes in playlist followers (RQ1), we assess how the pandemic influenced listener engagement across playlist types, providing insight into platform performance and potential shifts in exposure through playlists. Investigating the impact on playlists with different levels of popularity[1] (RQ2) helps determine whether the pandemic intensified or narrowed disparities between highly followed and niche playlists. Examining variation in resilience across curators (RQ3), who differ in their resources and promotional capacity, sheds light on how stakeholders managed follower retention and growth during the pandemic. Finally, evaluating whether playlists with a higher share of major label content gained more followers (RQ4) reveals how established industry players may have sustained or strengthened their influence over streaming behavior. Together, these questions provide insights into how the pandemic may have influenced the relative visibility and engagement outcomes for different stakeholders, with potential implications for platform dynamics and industry structure.

To answer our research questions, we estimate weekly changes in Spotify playlist followers before and after the COVID-19 pandemic declaration, focusing on shifts in overall follower counts across playlists with different popularity levels, curated by different curators, and having varying proportions of major label content. We utilize playlist information from Spotify covering playlists from October 2019 to October 2020, sourced from *Chartmetric.com* for playlist-level follower data and *Everynoise.com* for playlist feature information. The latter feature data captures instances when playlists are promoted on the Spotify user interface (i.e. Browse or Search Page). Controlling for this promotional information enables us to distinguish organic follower growth from gains driven by platform-driven exposure. We employ a unit fixed effects model to control for the time-invariant characteristics of playlists and account for pandemic-related variation (Papies et al., 2022; Papies & van Heerde, 2017) using three complementary measures: a binary indicator for the official pandemic declaration date, a country-weighted government stringency index, and a

[1] In the music industry literature, highly popular playlists are often linked to the broader superstar phenomenon (Rosen 1981; Elberse 2008). We use the term top-tier playlists to remain consistent with our empirical categorization while drawing conceptually on this literature in Section 2.2.

country-weighted residential mobility index. The first measure captures the average shift in playlist engagement following the initial pandemic declaration, while the other two reflect the evolving impact of government restrictions and public mobility patterns. Together, these indicators help us assess how varying lockdown measures and behavioral shifts influenced user engagement across different types of playlists and stakeholders.

Our findings suggest structural shifts in playlist follower engagement during the COVID-19 pandemic, offering empirical insights into how user behavior and stakeholder visibility evolved. Although we found no significant change in the average rate of follower growth after the pandemic declaration (RQ1), follower growth responded positively to increased time spent at home and stricter government restrictions, implying that playlist engagement was more sensitive to behavioral shifts than to the pandemic event itself. We found that follower changes varied substantially across popularity levels (RQ2). Playlists from upper mid-range in the top 5% and lower gained relatively stronger growth, while "superstar" playlists in the top 0.1%, which account for over 50% of all followers, did not experience additional gains. This indicates that follower growth during the pandemic was less concentrated at the top, leading to a more even distribution of engagement across playlists. We also observe significant differential effects across curator type (RQ3). Spotify-curated playlists were evidently more resilient to pandemic-related shifts than those curated by other curators. This advantage held even after accounting for platform-featured promotion, pointing to Spotify's strong position as both platform and curator. Finally, while playlists with a higher share of major label content did show some positive association with follower growth, the effects were relatively small and ultimately overshadowed by track-level popularity (RQ4). Once we accounted for how frequently tracks appeared across playlists, the role of label affiliation diminished. This suggests that users engaged more with recognizable tracks than with brand-based cues.

The rest of the paper is organized as follows. Section 2 reviews prior research on music streaming platforms, playlist influences, and the impact of the COVID-19 pandemic. This section highlights research constructs and gaps that motivate our analysis. Section 3 introduces the empirical context of this study, describes the dataset, and details the variable operationalization used to answer our research questions. Section 4 details our identification strategy and presents estimation results from a unit fixed effects model, focusing on differences in playlist follower changes across curator types, popularity tiers, and content composition. Section 5 synthesizes the main findings, draws out implications for platforms and curators, and discusses limitations and directions for future research.

2 Background and Conceptual Framework

Previous literature in marketing has long examined how crises affect consumer behavior and firm outcomes. Studies on product-harm crises emphasize firm- or product-specific faults that trigger blame attribution and recovery strategies (Cleeren et al. 2017; Khamitov et al. 2020). The COVID-19 pandemic, however, differs fundamentally from these contexts: it was a systemic, exogenous disruption without a culpable firm, simultaneously affecting entire industries. Recent articles highlight how pandemics reshape marketing more broadly, often in retailing and marketing strategies implementation. For example, Das et al. (2021) discusses how COVID-19 affected the marketing mix and opened new research opportunities related to consumer behavior, branding, and digital platforms. Roggeveen and Sethuraman (2020) highlights pandemic-induced changes in retailing practice, such as the acceleration of online grocery shopping, shifts in consumer preferences, altered demand for luxury versus value-oriented brands, and the redesign of in-store experiences and employee safety measures. Although this literature stream sheds light on pandemic-related changes in retailing strategies and consumer behavior, it does not directly extend to platform-based contexts. Some implications can be drawn. For instance, playlist curation in streaming may be seen as analogous to product strategy in retailing. Yet the nature of consumption differs. While retailing focuses on transactions, streaming engagement depends on ongoing visibility and following, which shape exposure opportunities for artists and curators. As such, existing retail-oriented insights provide only limited guidance for analyzing how stakeholders in music streaming were affected.

This limitation leads to the need for studies that complement marketing and retailing perspectives by focusing on engagement within digital platforms. Prior studies have highlighted the importance of playlists in shaping music consumption and artist visibility. Datta et al. (2018) emphasized how streaming platforms drive variety and demand, while Aguiar & Waldfogel (2021) and Pachali & Datta (2024) demonstrated a strong link between playlist followers, streaming activity, and music discovery. However, most of this work draws on broader platform settings, offering limited empirical insight into how playlist engagement shifts under external shocks, such as the COVID-19 pandemic, which disrupted typical consumption patterns, shifting listening away from traditional formats and toward more reliance on digital platforms. Although COVID-19 has affected music consumption, its influence on playlist followers has received limited attention. Table 1 summarizes relevant studies examining music consumption across formats, with a focus on five aspects related to our research questions: the unit of analysis, dependent variable, consumption formats, stakeholder focus, and whether the study considers pandemic-related effects. These aspects help frame our empirical reasoning and highlight gaps in existing research.

Relevant studies have typically analyzed songs or albums (unit of analysis) using outcomes such as play counts or revenue (dependent variables), within a single consumption format or across multiple formats. In contrast, we focus on playlists and use playlist followers as a measure of user engagement and visibility within streaming platforms. Although some existing work includes curators or labels as stakeholders, few studies differentiate how various curator types, including platforms, major labels, or independent entities, performed within music streaming platforms under pandemic conditions. Similarly, artists and smaller curators remain underexplored, especially regarding how playlist composition shaped exposure during this period. Finally, while some studies take place during the COVID-19 period, few directly assess how the pandemic influenced follower dynamics, whether through an aggregate shift (RQ1), variation by playlist popularity (RQ2), differential curator resilience (RQ3), or content-level effects (RQ4).

Study	**Unit of Analysis**	**DV (Dependent Variable)**	**Format**	**Stakeholder**	**Pandemic Effect**
Papies & Van Heerde (2017)	Recorded Music, Concerts	Sales, Revenue	Physical, Digital	Labels	-
Datta et al. (2018)	Songs	Play counts, Variety	Streaming	-	-
Yeung (2020)	Songs	Streaming counts	Streaming	-	x
Boughanmi & Ansari (2021)	Albums	Success score	Digital, Physical	Labels, Artists	-
Aguiar & Waldfogel (2021)	Songs	Streaming counts	Streaming	Curators	-
Sim et al. (2022)	Songs	Streaming counts	Streaming	-	x
Denk et al. (2022)	Music Listeners	Time & money spent on music	Streaming, Physical	-	x
Pachali & Datta (2024)	Playlists	Followers	Streaming	Curators, Labels	-
This Study	Playlists	Followers	Streaming	Labels, Curators, Artists	x

Table 1: Summary of relevant literature on music industry and the effect of COVID-19 pandemic

By focusing on playlist-level changes, accounting for different effects across playlists' popularity, curator types, and content characteristics, in response to variation in pandemic-specific indicators, this study provides empirical insight into how COVID-19 reshaped platform engagement via playlist consumption and subsequent stakeholder visibility. To guide the analysis, the following four subsections revisit each of the research questions introduced earlier, situating them within the relevant literature and outlining their empirical motivation.

2.1 Overall Changes in Playlist Followers

First, we examine whether playlist engagement, which is captured by follower counts, declined, increased, or remained stable during the pandemic.

Previous research shows that streaming platforms such as Spotify experienced significant shifts in usage during the COVID-19 pandemic, largely driven by changes in users' daily routines (Sim et al., 2022; Denk et al., 2022). In particular, studies find that audio consumption, especially music streaming, declined in the early phase of the pandemic, likely due to reduced commuting and other mobile activities that typically accompany music listening. These patterns suggest a potential decrease in music engagement across all consumption formats.

Since playlist followers are strongly associated with listener engagement (Aguiar & Waldfogel, 2021), a decline in streaming activity may also indicate lower follower growth, or even a loss of followers, for many playlists. Yet, the number of music streaming subscribers continued to rise globally in 2020 (MIDia Research, 2024), raising the possibility that users remained on platforms despite consuming less content. This disconnect between user base growth and actual usage may stem from behavioral inertia or subscription stickiness (Rietveld & Schilling, 2020), complicating expectations about average engagement metrics, particularly in terms of playlist followers..

Given this contradictory evidence, which is declining usage but rising subscriptions, it remains unclear what happened to playlist followers on average. Users may have consumed less content while retaining their subscriptions, highlighting the need for a longitudinal empirical analysis to uncover actual patterns of engagement during the pandemic. This leads to our first research question: *How did the number of followers for playlists change during the pandemic?*

2.2 Playlist Popularity and the Superstar Effect

We next explore whether the pandemic reshaped the distribution of engagement across playlists with different levels of popularity, from highly followed playlists, which we empirically categorize as "top-tier" but can be conceptually linked to the well-known "superstar" phenomenon in the music industry (Rosen, 1981; Elberse, 2008), to lesser-known long-tail ones.

On streaming platforms, the highly skewed concentration of playlist engagement is evident in playlist follower distributions. A small number of highly popular playlists, which are typically curated by platforms or major labels, attract the bulk of followers, while the majority of playlists make up a long tail of niche, less-followed content (Aguiar et al., 2021; Pachali & Datta, 2024). This reflects the broader "superstar effect," a phenomenon where a few products or producers dominate consumer engagement, often exacerbated by algorithmic promotion and user inertia (Knox & Datta, 2022; Rietveld & Schilling, 2020).

At the same time, digital platforms enable the coexistence of both superstar and niche content by reducing search costs and expanding the variety of accessible music (Brynjolfsson et al., 2010; Datta et al., 2018). This more democratized access supports not only a handful of widely followed "superstar" playlists but also a much broader set of moderately followed ("mid-tail") and niche ("long-tail") playlists. The mid-tail refers to playlists that have a moderate but still notable follower base, while the long-tail consists of the vast majority of playlists with small or specialized audiences. These less prominent playlists can gain visibility as users explore new genres, moods, or activities.

It is possible that the COVID-19 pandemic shifted the distribution of attention across playlists by changing users' listening habits. As commuting and social routines were disrupted, listeners may have changed how and when they used streaming services. On one hand, these changes could have reinforced existing habits, with users relying more heavily on familiar and prominently featured playlists, leading to an amplification of the superstar effect. On the other hand, increased time at home may have encouraged more exploration, leading users to seek out new music and niche content, potentially boosting engagement with mid- and long-tail playlists.

These competing dynamics introduce ambiguity that can be resolved through empirical testing of playlist follower changes across popularity tiers. Did users concentrate on popular playlists, or did they diversify their listening habits? This leads to our second research question: *How did the pandemic impact playlists across different levels of popularity?*

2.3 Curator Type and Follower Resilience

We next examine whether playlists curated by different types of stakeholders including platforms, major labels, independent curators, artists, and users, showed different levels of resilience in retaining or growing followers during the pandemic.

Streaming platforms like Spotify play a central role in shaping how users discover and engage with media. Leveraging extensive user data, these platforms can algorithmically curate playlists that match listener preferences, reinforcing engagement across both popular and niche segments (Datta et al., 2018; Datta & Knox, 2022). Through selective promotion on their user interfaces, such as highlighting playlists on the homepage, genre tabs, or personalized recommendations, platforms can direct user attention to specific content (Panico & Cennamo, 2022; Rietveld et al., 2019). This ability to engineer discovery may give platform-curated playlists a unique advantage in weathering adverse situations such as the COVID-19 pandemic.

Prior studies suggest that users tend to favor playlists curated by the platform itself, likely due to their visibility and personalized appeal (Aguiar et al., 2021; Pachali & Datta, 2024). These advantages may have helped platform-curated playlists retain or even grow their follower base during a time of uncertain routines and potential changing media habits. Even though other curators including major labels, professional tastemakers, artists, and everyday users, contribute to playlist diversity, they differ significantly in their ability to promote content. Major record labels, for example, can use both platform tools and external marketing to boost engagement (Boughanmi & Ansari, 2021), while smaller curators typically rely on organic discovery. Artist- and user-generated playlists may be even more constrained, often lacking algorithmic visibility or institutional support. These differences suggest that curator type could be an important determinant of how well playlists sustained engagement during the pandemic.

In this study, we define resilience as a playlist's ability to maintain or increase its follower count in the face of pandemic-related disruptions. Given the varying resources and strategic capacities of curators, it remains an open question whether some types were systematically more resilient than others. This leads to our third research question: *How did playlists curated by music streaming platforms, major labels, artists, professional curators, independent curators, and users differ in their resilience to changes in follower numbers during the pandemic?*

2.4 Content Composition and Major Label Influence

In addition to who curates a playlist, what content it features may also shape follower shifts during the COVID-19 pandemic.

A playlist's composition, particularly its share of tracks from major versus independent labels, can affect how appealing it is to users. Major labels, such as Universal Music Group, Sony Music Entertainment, and Warner Music Group, have long dominated the recorded music industry and continue to provide much of the most visible content on streaming platforms. Tracks from these labels benefit from brand recognition, high production quality, and familiarity, which can influence listener behavior even when users are not aware of the curator. Prior research suggests that listeners treat major label songs as "search tracks", being reliable and easily evaluated options that help reduce uncertainty in music selection (Mu et al., 2018).

During the pandemic, when many users faced greater uncertainty and changing routines, playlists featuring a higher proportion of major label content may have gained an advantage. With limited access to live performances and fewer alternative channels for discovery, listeners might have gravitated toward playlists that featured recognizable, high-profile content. Playlists with a greater share of major label tracks, regardless of who curated them, may have offered a sense of reliability or comfort in an otherwise uncertain media environment. In contrast, playlists featuring primarily independent content may have faced greater challenges in attracting or retaining followers. This study empirically evaluates whether playlists with greater major-label representation actually retained or attracted more followers, providing evidence on the effectiveness of content branding under pandemic conditions.

This distinction between branded content and lesser-known material offers an insight into how playlist composition itself, apart from its visibility or curator, influences user engagement. We therefore ask: *Did playlists featuring a higher proportion of tracks from major labels experience an increase in followers during the pandemic?*

3 Data

To examine how the COVID-19 pandemic affected playlist engagement on music streaming platforms, we used a dataset collected from Spotify, the industry's leading service. We rely on weekly changes in playlist followers to capture how user behavior evolved during the pandemic and how that behavior may have influenced the visibility and positioning of different stakeholders within the platform. This section introduces the platform context, describes our dataset, and explains how our variables are operationalized to empirically answer the study's four research questions: overall changes in follower engagement (RQ1), variation across playlist popularity (RQ2), resilience across curator types (RQ3), and the influence of major label content (RQ4).

3.1 Background on Music Streaming Platforms

The music industry is dominated by digital streaming services, which accounted for 83 percent of total revenue in the US (RIAA, 2021) and 62.1 percent worldwide (IFPI, 2021) by the end of 2020. These streaming services allow users to access millions of tracks and playlists that can be produced and curated by anyone on the platform. They have been a major form of music consumption in the US since the mid-2010s. Among these platforms, Spotify is the global market leader, with a total of 381 million global users and 172 million subscribers (MIDiA Research, 2022).

Users can browse tracks, albums, and playlists through an intuitive interface. Playlists, which are lists of tracks curated by various entities, serve as key tools for organizing content around particular themes, genres, or moods, allowing users to discover and continually play curated selections of music (Pachali & Datta, 2024; Aguiar & Waldfogel, 2021). For instance, Spotify's "Rock Classics" playlist offers a selection of popular rock tracks curated by the platform itself. Spotify reports that playlists account for approximately 30% of its users' listening time (Pachali & Datta, 2024), highlighting their importance for user experience and platform engagement.

Users can "follow" playlists, enabling them to access these playlists easily in their libraries and stay updated with any changes. The following behavior not only reflects user interest and engagement, but also signals playlist visibility and influence. Playlist follower growth is driven in part by visibility and accessibility, which can result from either organic user search or platform-driven promotion. Users may find playlists by actively searching for specific themes, genres, or activities. At the same time, streaming platforms can amplify visibility by featuring selected playlists in prominent locations such as the homepage, genre tabs, or search interface. These featured placements can be organized around moods (e.g., "chill"), activities (e.g., "workout"), or genres (e.g., "pop") to help steer user attention and engagement toward selected content.

3.2 Sample

In this study, we analyze a sample of global playlists available on Spotify from 29 October 2019 to 4 October 2020. It covers 19 weeks before and 30 weeks after the World Health Organization's pandemic declaration on March 11, 2020.

In line with Pachali and Datta (2024), we rely on two primary datasets to assemble our sample:

(1) playlist-level follower data from *Chartmetric.com*, a third-party service that aggregates daily data from the Spotify Web API, which we aggregate into weekly intervals to observe follower changes over time, and (2) playlist feature data from *Everynoise.com/worldbrowser.cgi*, providing weekly snapshots of playlists featured on Spotify's Search Page to control for platform-driven promotion.

The *Chartmetric* dataset provides comprehensive follower data across a wide selection of Spotify playlists. Chartmetric collects information on playlist followers, track inclusions, and curator types, covering over 1.2 million playlists on Spotify as of April 2020. We use this dataset to track changes in playlist followers over time, selecting a subset of 151,039 active playlists to ensure broad representation of Spotify's ecosystem. This subset covers more than 90% of total followers on Spotify, providing a robust basis for analyzing changes of playlist followers over times.

To focus on consistently active playlists and ensure data continuity, we refine the sample further, selecting 104,835 playlists with 49 consecutive weeks of follower data. From this, we retain 39,918 playlists with complete metadata, with varying relevant attributes available. They include genre, curator type, and share of tracks from MLs and other playlist characteristics. This allows us to focus on playlists with sufficient information for analysis of changes in playlist followers, capturing a variety of playlist sizes, curators, and track compositions.

The *Everynoise* dataset complements this follower data by capturing weekly instances of playlists featured on Spotify's Search Page. Featuring on the Search Page is platform-driven promotion increasing a playlist's visibility and accessibility to users. We use this data to identify which playlists received this additional visibility, controlling for the effects of featuring when analyzing changes in playlist followers. By integrating these weekly featuring indicators, we can better isolate follower changes driven by organic user engagement from those influenced by platform-driven promotion.

While our study follows Pachali and Datta (2024) in leveraging data from *Chartmetric.com* and *Everynoise.com*, it extends beyond their sample by focusing on a broader set of playlist characteristics and covering a longer period. Specifically, Pachali and Datta's dataset primarily centers on playlists active until early 2020, with a focus on general drivers of playlist demand and popularity across Spotify. In contrast, our sample spans from October 2019 to October 2020, capturing the weeks before and several months after the COVID-19 pandemic declaration, allowing us to specifically analyze pandemic-related shifts in playlist follower.

Although Pachali and Datta's sample includes playlists curated by platforms and major labels, our study specifically examines the role of different curators, incorporating playlists curated by independent labels, individual artists, professional curators, and users. This broader focus enables us to explore potential differences in pandemic impacts across curator types. Furthermore, while Pachali and Datta emphasize individual tracks by major label artists and popular songs, our study analyzes playlist-level composition, examining the proportion of major label versus independent tracks within playlists. This approach allows us to assess whether content composition within playlists influenced follower dynamics, offering new insights into content-driven engagement beyond Pachali and Datta's focus on song-level popularity.

We report summary statistics of our playlist sample by curators in Table 2. Based on our sample, most popular playlists are Spotify-curated. Major labels (MLs) as curators do not gain any disproportionate market share of followers in the playlist market compared to other curators. This is consistent with Pachali & Datta (2024) showing that playlist followers on Spotify are highly concentrated. This concentration supports our popularity investigation and reinforces the need to distinguish between top-tier "superstar" playlists and the broader long tail apart from the curator types. Our data also reveal substantial variation in playlist composition. Despite significant variations in the proportion of major label tracks across playlists over time in our study, on average, more than half of the tracks in playlists are from major labels, except in playlists curated by independent labels. Moreover, we observe that most of the playlists featured on Spotify's Search Page during the study period are Spotify-curated. To better understand whether these playlists attract followers organically, we include featuring as a control variable. This allows us to distinguish between follower growth driven by platform promotion and growth that may reflect underlying user interest or curator strength.

Table 2: Summary statistics of playlist sample curated by Spotify, major labels (MLs), artists, independent labels, other and users

Curators	Spotify	Pro curators	MLs	Artists	Indie Labels	Other	Users
# Playlists	3,504	4,834	2,195	5,626	1,399	18,032	4,328
Avg. Followers	217,546	14,400	10,511	10,085	8,291	4,443	569
Avg. Δ Followers	669	16	28	23	54	5	0.5
Number of playlist across different popularity (i.e., share of follower percentileth)							
# in Pr $\leq$ 0.1	608	18	1	16	2	0	0
# in 0.1< Pr $\leq$ 1	1,581	665	220	433	92	574	0
# in 1< Pr $\leq$ 5	856	1,678	880	2,185	524	8,412	1
# in 5< Pr $\leq$ 10	263	1,370	643	1,897	483	6,195	2,131
# in Pr > 10	196	1,103	451	1,095	298	2,851	2,196
Playlist attributes and features							
Avg. MLs Share	51.46	53.74	77.81	50.78	28.31	54.82	56.55
SD. MLs Share	29.71	27.29	17.31	31.91	29.60	26.93	26.21
Avg.TotalFeature	63.21	0.43	0.88	0.04	0.02	0.01	0.00

Notes: Reported across selected 39,918 playlists in our sample. The table reports the number of playlists curated by different curators, the average (Avg.) and its weekly change (Δ) in followers, the number of playlists across different popularity, measured in percentile ranks, the average and standard deviation (SD.) of major labels' tracks share (in %) across playlists over the study period and average number of times a playlist got featured on Spotify's Search Page.

3.3 Variable Operationalization

Our outcome variable is the weekly change in playlist followers, as this measure captures shifts in playlist engagement within the platform over time, allowing for a temporal view of how followers responded to pandemic-related changes. By examining weekly changes rather than static follower counts, we can observe engagement patterns that reveal short-term fluctuations in user interest, which might be overlooked when relying only on a single-point snapshot. A static count might capture an overall change but could miss significant shifts such as sudden drops or surges in followers. Such changes reflect real-time user responses to specific events or conditions during the pandemic. Looking at the change also helps address behavioral inertia in digital subscriptions when users often do not actively unsubscribe or unfollow due to frictions or low incentives to change.

We define several variables that capture the specific characteristics of playlists and help us answer the research questions. First, to assess the overall shift in engagement (RQ1), we incorporate COVID-19 indicators including a binary indicator for the official pandemic declaration date, a country-weighted government stringency index, and a country-weighted residential mobility index. These indicators capture the average shift in playlist engagement following the initial pandemic declaration and the evolving impact of government restrictions and public mobility patterns. Second, to explore whether playlists with varying levels of popularity experienced different follower shifts (RQ2), we classify playlists by popularity tiers based on their follower counts. Third, to examine differences in resilience across stakeholders (RQ3), we categorize playlists by curator types. These types include Spotify, major labels, independent labels, artists, professional curators, and users. Each type represents varying levels of resources and potential influence on the platform. Fourth, to test whether content composition affected engagement (RQ4), we include the share of major label tracks within each playlist, reflecting whether well-branded content helped retain or attract followers. Finally, we control for potential confounding factors such as playlist themes, platform-based promotion (e.g., Search Page features), and seasonal effects, which allow us to isolate the impact of the pandemic from other influencing factors. Table 3 provides details about the operationalization of the variables.

3.3.1 COVID-19

To capture the impact of COVID-19 on playlist followers, we employ a combination of pandemic indicators. Using a single date, such as the World Health Organization's pandemic declaration on 11 March 2020 ($CovidTime_t$), provides a clear start point for analyzing the initial effects. However, this date alone may oversimplify the pandemic's effects, especially when the evolving landscape of government restrictions and public mobility patterns could influence music consumption patterns over time. A single date indicator may miss the ongoing and variable impact of lockdowns, which altered mobility and user engagement behaviors as the pandemic progressed.

To address this, we include two additional measures that account for the variation in pandemic-related restrictions experienced by users worldwide. Building on the approach used by Sim et al. (2022), we calculated a country-weighted average government restriction index ($StringencyIndex_t$) and a country-weighted average percentage change in time spent at home ($Residential_t$). The Government Response Stringency Index from the Oxford COVID-19 Government Response Tracker quantifies government restrictions by factoring in measures such as school closures, workplace closures, and travel bans (Wenham et al., 2023), thus offering a more granular view of restriction intensity and timing across countries. The Google COVID-19 Community Mobility Report's *Mobility trends for places of residence* data ($Residential_t$) complements this by measuring changes in the amount of time individuals spent at home, reflecting users' exposure to and engagement with digital media during prolonged stay-at-home orders (Google, 2022).

Given that our data contains only playlists available to a global audience, constructing country-weighted measures for both $StringencyIndex_t$ and $Residential_t$ allows us to reflect the influence of restrictions based on the relative streaming activity from each country. A simple unweighted average would not capture the variations in user engagement across different regions; thus, we apply country weights to emphasize the proportional impact of each country's restrictions according to its streaming volume. This approach gives greater weight to countries with higher streaming activity, aligning our metrics with the international scope of our playlist sample.

We calculate the country-weighted government restriction and residential mobility indices as follows:

$StringencyIndex_t = \sum w_{c,t} * StringencyIndex_{c,t}$

$Residential_t = \sum w_{c,t} * Residence_{c,t}$

where $w_{c,t}$ is the proportion of total streams of the top 200 streamed songs in country c in period t relative to the total top 200 streamed songs across all available countries. This country-weighted structure enables us to capture the dynamic and regionalized effects of the pandemic on playlist followers, reflecting how varying restrictions influenced playlist engagement within the platform globally.

Integrating these three indicators, pandemic declaration date, government restriction levels, and residential mobility changes, allows us to estimate the varying impacts of COVID-19 on playlist followers. The variations of these factors enable us to analyze not only the overall average effects of the pandemic but also the influence of ongoing restrictions and behavior shifts on streaming platform engagement.

3.3.2 Playlist Popularity

To assess the impact of the COVID-19 pandemic on playlists with varying levels of popularity, we categorize playlist popularity according to follower counts, capturing different levels of prominence within the music streaming platform. This approach enables us to distinguish between highly popular 'superstar' playlists, moderately popular 'mid-tail' playlists, and 'long-tail' playlists with smaller follower counts. These categories reflect differing levels of initial popularity and visibility across Spotify.

Following Elberse and Oberholzer-Gee (2006), Brynjolfsson et al. (2011), and Kumar et al. (2014), we utilize percentile ranks of follower counts to capture these dynamics. Based on a comprehensive list of approximately 1.2 million playlists tracked in April 2020, we define five popularity groups as follows:

Top 0.1% – "Superstar" playlists. These account for over 50% of total followers despite representing a tiny share of all playlists.

0.1% to 1% – Highly popular playlists just below the superstar tier. Together, the top 1% of playlists account for roughly 80% of all followers.

1% to 5% – "Mid-tail" playlists with moderate followings. Cumulatively, the top 5% of playlists account for about 97% of all followers.

5% to 10% – Lower mid-tier playlists with more limited reach. The top 10% of playlists together account for approximately 99% of followers.

Bottom 90% – "Long-tail" playlists with niche or small audiences. Collectively, they represent the remaining 1% of total followers.

This categorization reflects the highly skewed follower distribution typical of digital platforms, where playlist follower's distribution is concentrated among a few top entities. Using data from April 2020 as a baseline for categorization is appropriate because it reflects follower distribution shortly before the pandemic's widespread impact on global routines and media consumption patterns. This timing allows us to capture playlists' established popularity without significant pandemic-driven influences. By excluding playlists introduced after April 2020, we ensure that our sample includes only those playlists active prior to the pandemic, creating a stable reference for analyzing changes in followers. This approach enables us to assess whether the pandemic intensified the superstar effect, with popular playlists gaining even more traction, or contributed to a more balanced engagement across niche, long-tail playlists.

3.3.3 Curators

To address our research question on playlist curators and the pandemic's impact on playlist followers, we categorize playlists based on curator types. This enables us to investigate whether playlists curated by different stakeholders demonstrated varying resilience or experienced distinct advantages during the pandemic. Specifically, our study examines whether well-resourced curators like Spotify and major labels retained or increased their follower growth more effectively than less-resourced groups, such as independent labels and user-generated playlists.

Pachali and Datta (2024) provide a classification of curators that we directly adopt to differentiate playlists by curator type in our analysis. While their study uses this classification to explore general playlist popularity and demand, we place curator type at the center of our analysis to examine differential impacts of the pandemic on follower engagement across these groups. Using their categorization, we classify curators as follows:

Spotify: Playlists curated directly by Spotify, often by in-house teams specializing in global music trends, account for much of the platform's popular content. These playlists generally feature a significant proportion of tracks by the label's artists, which may enhance visibility and engagement.

Major Labels: Major record labels, including Universal Music Group, Sony Music Entertainment, and Warner Music Group, curate playlists under label-specific brands such as "Digster" for Universal, "Filtr" for Sony, and "Topsify" for Warner. These playlists typically incorporate a higher proportion of tracks from the respective labels' artists, which may contribute to their visibility and follower retention within the platform.

Independent Labels and Artists: Independent labels and individual artists curate playlists under their own names or smaller label brands.

Professional Curators: Professional curators, sometimes known as "tastemakers," include brands, media companies, or radio stations that create playlists to complement their brand or broadcast content. As defined by Pachali and Datta (2024), tastemakers have a reach of at least 50,000 followers, indicating a notable level of platform influence.

Users and Other Curators: User-created playlists, typically designed for personal music organization, have a reach of 1,000 followers or fewer. The "Other Curators" category includes playlists that do not fit the previous classifications, covering a diverse range of less common playlist types.

By examining changes in playlist followers across these curator types, we assess whether curators with greater algorithmic visibility, promotional resources, or brand recognition were better able to retain or grow their audiences during the pandemic, providing empirical insights on stakeholder resilience and competitive dynamics within the platform ecosystem.

3.3.4 Major Labels Share

The global music industry is significantly shaped by the influence of three major recorded labels: Universal Music Group, Sony Music Entertainment, and Warner Music Group. Together, these companies held more than 68 percent of the total recorded music market share worldwide in 2020 (Music & Copyright, 2021), demonstrating their dominance in the industry. To explore the impact of major label presence within playlists on follower change during the pandemic, we measure the proportion of major label tracks within each playlist rather than counting individual tracks or focusing on specific, high-profile artists.

This approach offers a few key advantages. First, by focusing on the share of tracks from major labels rather than the number of songs or specific artists, we establish a consistent metric that allows for comparison across playlists of various sizes and compositions. This metric better captures the general influence of major labels across playlists without conflating results with individual superstar effects. Although previous research, such as Pachali and Datta (2024), has found that superstar artists from major labels can influence playlist popularity, our study is concerned with the broader impact of major label presence on playlist follower growth. By examining the aggregated share of major label tracks, we aim to understand whether playlists with a greater proportion of content from well-established labels demonstrated resilience or increased appeal during the pandemic period.

The long-standing market presence of these three major labels, with roots extending back to the 1970s (Smith & Telang, 2016), suggests that their inclusion within playlists serves as a quality signal. Playlists featuring a higher share of major label tracks are likely perceived as containing reliably curated, popular, or high-quality content, benefiting from these labels' established brand reputations and promotional reach. This signal of quality could make such playlists more appealing to users, especially in uncertain times when familiar content might be preferred. This aligns with our research question on whether major label tracks could potentially attract more followers during the pandemic, shedding light on how content composition within playlists influenced engagement levels in response to changes in listening behaviors.

3.3.5 Control Variables

To ensure an accurate analysis of how COVID-19 impacted playlist followers, we include several control variables that could otherwise influence follower dynamics independently of our primary variables of interest. By controlling for these factors, we aim to isolate the effects of playlist popularity, curator type, and major label track share, which are central to our study's research questions.

First, we control for playlist categorization, as playlists associated with different genres, moods, and activities likely attract distinct listener demographics and engagement levels. Following the categorization method established by Pachali & Datta (2024), we assign each playlist to one or more of 32 categories observable on Spotify's Search Page, which plays an integral role in Spotify's discovery and curation processes. These categories include genre-based themes (e.g., "Afro," "Jazz"), mood-based themes (e.g., "Chill," "Romance"), and activity-based themes (e.g., "Workout," "Dinner"), all significant to how users navigate playlists on the platform. Our selected categories span a broad range of musical themes and use cases, such as: (1) Activity, (2) Afro, (3) Anime, (4) Arab, (5) Blues, (6) Chill, (7) Classical, (8) Country, (9) Dance, (10) Desi, (11) Dinner, (12) EDM, (13) Focus, (14) Funk, (15) Gaming, (16) Hip Hop, (17) Indie, (18) Inspirational, (19) Jazz, (20) K-pop, (21) Latin, (22) Metal, (23) Mood, (24) Party, (25) Pop, (26) Punk, (27) R&B, (28) Rock, (29) Romance, (30) Sleep, (31) Soul, and (32) Workout.

The integration of these thematic categories reflects the diverse interests and consumption patterns of Spotify's users. For instance, genre-based playlists such as "Pop" might attract a broader audience and maintain greater follower stability, while activity-based playlists like "Workout" may see more fluctuations in engagement, especially as user routines shifted during the pandemic. By controlling for these thematic categories, we aim to reduce potential confounding effects, ensuring our analysis accurately isolates the impacts of curator type, playlist popularity, and major label composition on follower dynamics.

Second, we control for the effect of being featured on Spotify's Search Page. Playlists featured prominently on the platform receive enhanced visibility, which can drive significant gains in follower counts (Pachali & Datta, 2024; Aguiar & Waldfogel, 2021). This feature effect could amplify follower engagement regardless of a playlist's popularity or curator type, potentially obscuring the specific impact of pandemic-induced shifts. Including this control helps clarify whether any observed resilience or growth in followers is due to feature-driven exposure rather than intrinsic characteristics of the playlist or its curator.

Third, we control for seasonal and time-based trends by including variables for the months of the year and specific weeks within our study period. These controls account for general growth trends in platform usage as well as any seasonal variations that could affect streaming activity across the year. By incorporating these temporal factors, we aim to isolate the impact of the pandemic on follower growth, reducing the potential influence of natural growth patterns and seasonality on our analysis.

Together, these control variables allow us to isolate the effects of playlist composition, curator identity, and popularity levels, providing a robust framework for assessing how the pandemic influenced follower dynamics across different stakeholder groups and playlist types.

Table 3: Variable Operationalization

Variable	Operationalization
Dependent Variable	
Δ Followers$_{i,t}$	A weekly change in number of follower of playlist i in period t compare to period t-1.
Independent Variables	
CovidTime$_t$	Step dummy variable indicating the beginning of the pandemic, equaling 1 if period t is after 11 March 2020, 0 otherwise.
StringencyIndex$_t$	Country-weighted average government restriction in period t rescaled to a value from 0 to 100 (100 is strictest response). $StringencyIndex_t = \sum w_{c,t} * StringencyIndex_{c,t}$ where $w_{c,t}$ is the proportion of total streams of top 200 streamed song in country c in period t relative to total top 200 streamed songs across all recorded countries
Residential$_t$	Country-weighted average percentage change of time spent at home from the baseline in period t. $Residential_t = \sum w_{c,t} * Residence_{c,t}$ where $w_{c,t}$ is the proportion of total streams of top 200 streamed song in country c in period t relative to total top 200 streamed songs across all recorded countries
Popularity$_i$	Categorical variable indicating the popularity of playlist i. Playlist i either be (1) Playlists from first top 0.1% covering 52% of total followers (2) Playlists from the the top 0.1% to the top 1% covering 84% of total followers (3) Playlists from the top 1% to the top 5% covering 97% of total followers (4) Playlists from the top 5% to the top 10% covering 99% of total followers and (5) Playlists that are not included in top 10%
Curator$_i$	Categorical variable indicating the curator of playlist i. Playlist i either be curated by (1) Spotify, (2) the major recorded labels (MLs), (3) artists, (4) independent labels, (5) professional curators, (6) users and (7) others
MLShare$_{i,t}$	The percentage of tracks produced by Universal Music Group, Sony Music Entertainment, or Warner Music Group for playlist i in period t
Control Variables	
Categorization$_{ik}$	Categories of playlist i operationalized as grand-mean centered variable (%) for category k in all selected 32 categories. The measure implies the difference from the average proportion of all playlists that belongs to a certain category or the degree of being able to substitute to a particular genre.
Featured$_{i,t}$	On average, how many times playlist i got featured in a session on Spotify's Search Page across countries in period t.
Month$_t$	months of the year in period t.
Time$_t$	Time trend for period t.

4 Empirical Analysis and Results

4.1 Identification Strategy

Although the pandemic represents an exogenous shock to Spotify's ecosystem, identifying its impact requires addressing several challenges. First, because the pandemic affected all playlists at the same time, we lack a conventional control group with untreated units for a difference-in-differences analysis. Second, because our sample is limited to global playlists, we miss the potential for observing variations in engagement that country-level playlists might reveal. With country-specific playlists, we could observe how regional differences in government responses and mobility restrictions at a given time directly influenced playlist followers, offering a clearer picture of localized pandemic effects.

To address these challenges, we employ a unit fixed effects model on playlists, which effectively controls for time-invariant playlist-specific characteristics that may influence follower dynamics (Papies et al., 2022). This approach is appropriate for our analysis due to the following reasons:

First, by estimating the model with playlist (i.e., unit) fixed effects, identification relies on within-playlist variation over time. This means that each playlist's pre-pandemic follower trajectory functions as its own counterfactual benchmark, eliminating bias from time-invariant unobserved heterogeneity. The lack of a separate untreated group is thus mitigated by using historical patterns of the same unit as the basis for comparison. Second, the model accounts for unique, unobserved attributes of each playlist, such as its danceability attributes or curation styles, which could independently affect follower engagement regardless of pandemic influences. By controlling for these time-invariant characteristics, our model isolates changes in follower counts that are attributable to pandemic-related shifts. Third, the model includes weekly time controls, which capture platform-wide trends and other temporal fluctuations that may impact playlist engagement. This enables us to disentangle the pandemic's impact on playlist followers from growth trends, seasonal variations, and other time-based influences. Identification therefore comes from deviations in follower growth within the same playlist during the pandemic relative to its own pre-pandemic baseline, net of seasonal and platform-wide fluctuations.

While our data are aggregated at the playlist level and do not include direct country-level identifiers, we account for international variation in pandemic exposure by constructing country-weighted indices of government stringency and residential mobility. These indices reflect the relative streaming volume from each country, giving more weight to countries with higher user activity. This approach allows us to indirectly capture the influence of country-specific restrictions and behavioral shifts on global playlists, aligning the pandemic measures with the geographic distribution of actual engagement. Although we cannot observe individual country-level playlist trends, this weighting strategy ensures that our analysis incorporates meaningful cross-country variation in pandemic-related disruptions.

In summary, our identification strategy combines a unit fixed effects model, weekly time controls, and carefully defined control variables (including genre categories) to capture unique, time-invariant characteristics of each playlist while isolating the specific impacts of the pandemic on playlist followers.

4.2 Empirical Model

To assess the impact of the COVID-19 pandemic on playlist followers and examine how different stakeholders, including curators, content producers, and playlists with different levels of popularity, were affected, we employ a log-log model with (unit) fixed effects. This specification allows us to interpret the estimated coefficients as elasticities (Papies & van Heerde, 2017), capturing the relative changes in playlist followers in response to pandemic-related factors. The log transformation also helps correct for the skewed distribution of follower counts, particularly across playlists of vastly different popularity tiers. Our model is designed to address the four research questions by isolating within-playlist changes while controlling for time-invariant characteristics and time-specific effects. It also enables us to test for differential effects across playlists grouped by (percentile-based) popularity, curator type, and content composition. The model is specified as follows:

$$
\begin{aligned}
\Delta ln(Follower_{i,t}) = {} & \kappa Covid_t \\
& + \sum_{j=1}^{4} \gamma_j Covid_t \times Popularity_i \\
& + \sum_{k=1}^{6} \beta_k Covid_t \times Curator_i \\
& + \eta_1 MLShare_{i,t} + \eta_2 Covid_t \times MLShare_{i,t} \\
& + \sum_{l=1}^{32} \alpha_l Covid_t \times Categorization_{ik} + \alpha_{33} lnFeatured_{i,t} \\
& + \alpha_{34} Month_t + \alpha_{35} lnTime_t + \varepsilon_{i,t}
\end{aligned}
$$

In this specification, $Covid_t$ represents the pandemic-related variable, defined in three indicators: $CovidTime_t$ (pandemic declaration date), $StringencyIndex_t$ (weighted government restriction index), and $Residential_t$ (weighted time spent at home). Each measure of $Covid_t$ enables us to explore how different aspects of the pandemic affected follower engagement. Specifically, κ reflects the fixed effect of the pandemic declaration, government restrictions, and changes in home-based activity on changes in followers.

The interaction terms $Covid_t \times Popularity_i$ capture the pandemic's differential impact across playlists with varying levels of popularity, allowing us to assess whether highly followed "superstar" playlists (top 0.1%), moderately followed "mid-tail" playlists, or niche "long-tail" playlists exhibited different follower trends. Similarly, $Covid_t \times Curator_i$ measures pandemic effects across curator types, capturing whether playlists curated by Spotify, major labels, or other stakeholders showed varying resilience or follower growth in response to the pandemic.

We include the variable $MLShare_{i,t}$ to measure the influence of major label content in playlists. The interaction $Covid_t \times MLShare_{i,t}$ allows us to assess whether playlists with a higher share of major label tracks were particularly resilient or attractive to followers during the pandemic, especially given the perceived quality associated with major label content.

The $Covid_t \times Categorization_{ik}$ interaction terms control for playlist categorization (e.g., genre, mood, or activity), which ensures our analysis focuses on changes in playlist followers specific to curator type, popularity, or major label composition rather than thematic variations. Additionally, the $ln(Featured_{i,t})$ variable controls for any playlist featured on Spotify's Search Page, which often results in significant follower gains. By isolating these effects, we can distinguish feature-driven gains from organic user engagement during the pandemic.

The model also incorporates monthly and weekly controls to account for seasonal trends and overall platform growth over time. The inclusion of these controls helps ensure that our estimates reflect the pandemic's specific impact on follower engagement, adjusting for temporal trends in playlist engagement on streaming platform.

Given the absence of an untreated control group and the global nature of Spotify's audience, we use a unit fixed effects model to control for unobserved playlist-specific characteristics that may influence follower trends independently of the pandemic. This approach stabilizes any time-invariant, and playlist-specific factors in order to ensure that our results capture only within-playlist changes in response to pandemic-related shifts in user behavior.

4.3 Results

Table 4 shows the estimated fixed effects of the pandemic on playlist followers across different popularity and relevant platforms' stakeholders, including curators and track producers. Using a unit fixed effects model, we analyze how the pandemic declaration, global government restrictions, and changes in time spent at home globally influenced playlists across different curator types and popularity levels. To facilitate interpretation, we reported total estimated effects for playlists by curator and popularity category, as illustrated in Figure 1 - 3.

Columns (1), (3), and (5) in Table 4 indicate the average pandemic effects (i.e., pandemic declaration, global government restrictions and global changes in duration spent in places of residence) on playlist followers addressing our first research question on changes in playlist followers on the streaming platform. Meanwhile, Columns (2), (4), and (6) explore effects across different platform stakeholders, examining variations by curator type, playlist popularity, and major label track share.

It is worth noting that while the $MLShare$ variable shows statistical significance in some cases, its effect size remains relatively small. Specifically, a 1% (or 0.01 unit) increase in the proportion of major label tracks within a playlist yields only modest shifts in follower growth, suggesting that this measure captures subtle adjustments rather than substantial changes in follower dynamics. We maintain this scale for $MLShare$ to ensure consistency across the model and facilitate direct comparisons with other variables.

In the following sections, we further discuss these results, first focusing on overall follower changes, followed by effects across popularity levels and curator types, and concluding with the impact of major label track share on follower growth. Since playlist popularity and curator type are often interdependent meaning that popular playlists are frequently curated by specific types of stakeholders (e.g., Spotify itself or major labels), we analyze these categories jointly rather than separately to more accurately reflect the combined influence of both factors on changes of playlist followers during the pandemic.

4.3.1 Effects on Playlist Followers

Even though the number of music streaming subscribers worldwide grew from 2019 to 2020, on average, we do not see any significant change in playlists' followers after the pandemic declaration (Column (1) in Table 4). However, there is a significant ($p < .05$) positive relationship between an increase in playlist followers and stay-home measures, including stricter government policies and more time spent in residential places (Columns (3) and (5) in Table 4). Specifically, during the pandemic period, assuming the mean (i.e., median) global stringency index equals 65 on a certain week, each playlist gets 0.0004% increase in followers. For a mean (i.e., median) increase of 8% in time spent at home during the pandemic, each playlist get 0.0024% increase in followers.

This relationship suggests that user engagement with playlists may have been influenced more directly by restrictions on mobility and the resulting increase in home-based activities rather than the announcement of the pandemic itself. The initial declaration may not have significantly impacted listening habits, as it was only over time, as restrictions tightened and people adjusted to prolonged periods at home, that users sought greater engagement with digital content like streaming playlists. This aligns with behavioral trends observed in other digital media, where consumption patterns shifted notably as people adapted to "stay-at-home" lifestyles. Additionally, the positive relationship with time spent at home may reflect a broader shift in daily routines. With reduced commutes and increased flexibility in working or studying from home, listeners may have sought new music experiences, exploring or following more playlists.

These findings suggest that while the pandemic declaration initiated the beginning of a shift in user behavior, it was the ongoing restrictions and home-based adjustments that likely played a more substantial role in driving increased engagement with playlists (via followers) over time.

Table 4: Estimated Results from a Unit Fixed Effects Model (Within Playlists)

Model:	CovidTime (1)	CovidTime[1] (2)	Stringency (3)	Stringency[1] (4)	Residential (5)	Residential[1] (6)
Covid_t^a	0.0002	-0.0007	0.00000**	-0.00001	0.00003**	0.00001
	(0.0001)	(0.0004)	(0.00000)	(0.00001)	(0.00000)	(0.00002)
$\text{Covid}_t \times$ Artists		-0.0019**		-0.00002***		-0.00003
		(0.0004)		(0.00001)		(0.00002)
$\text{Covid}_t \times$ Indie Labels		-0.0024***		-0.00003***		-0.00004
		(0.0005)		(0.00001)		(0.00003)
$\text{Covid}_t \times$ ML		-0.0018***		-0.00002***		-0.00002
		(0.0005)		(0.00001)		(0.00003)
$\text{Covid}_t \times$ Other		-0.0023***		-0.00003***		-0.00006***
		(0.0004)		(0.00001)		(0.00002)
$\text{Covid}_t \times$ Pro Curators		-0.0031***		-0.00004***		-0.00005***
		(0.0004)		(0.00001)		(0.00003)
$\text{Covid}_t \times$ Users		-0.0027***		-0.00004***		-0.00010***
		(0.0004)		(0.00001)		(0.00002)
$\text{Covid}_t \times$ top 1%		0.0001		0.00000		-0.00001**
		(0.0005)		(0.00000)		(0.00002)
$\text{Covid}_t \times$ top 1-5%		0.0019**		0.00003***		0.00007***
		(0.0006)		(0.00001)		(0.00003)
$\text{Covid}_t \times$ top 5-10%		0.0027***		0.00004***		0.00010***
		(0.0006)		(0.00001)		(0.00003)
Covid_t × Tail		0.0028***		0.00004***		0.00014***
		(0.0006)		(0.00001)		(0.00000)
MLShare^a		0.0000		0.00002		0.00003*
		(0.0000)		(0.00002)		(0.00002)
$\text{Covid}_t \times \text{MLShare}^a$		0.0000***		0.00000***		-0.00000***
		(0.0000)		(0.00000)		(0.00000)
Genre	Y	Y	Y	Y	Y	Y
Feature	Y	Y	Y	Y	Y	Y
Month	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y
Fit statistics						
Observations				1,917,624		
Adjusted R^2	0.0277	0.0279	0.0276	0.0279	0.0276	0.0278

1 Spotify is a based curator with superstar (top 0.1%*) playlists.*
a Coefficients reported as 0.0000 are rounded for presentation; exact estimates are smaller than 0.00001 but statistically significant.
Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.3.2 Effects on Playlist Curators across Different Popularity

We illustrated the average effects of the pandemic declaration, the effect of government restrictions (at the mean) and the effect of time spent at home (at the mean) on playlists' followers curated by different curators across different popularity in Figure 1, 2 and 3 respectively.

Estimated effects of the pandemic declaration (Figure 1) and government restrictions (Figure 2) on playlists curators and playlist popularity are consistent. Spotify did not experience any significant (i.e., inconclusive confidence interval including zero) negative impact and their playlists along the mid-tail (i.e., top 5^{th} - top 10^{th} of follower percentile) and long-tail gained significantly more followers, suggesting that playlists curated by the music streaming platform were resistant and favorable during the pandemic time. Specifically, on average, Spotify playlists in top 5^{th} percentile gain a 0.16% increase in their followers and over 0.2% increase for those in top 10% and along the long-tail.

Conversely, playlists curated by major labels, professional curators, and independent curators faced more challenges in maintaining their follower base. For instance, superstar playlists (top 0.1^{st} percentile) curated by major labels saw a decline of over 0.2% in weekly follower growth, translating to approximately 2,000 fewer followers for a playlist with a 1,000,000-follower base. Professional and independent curators appeared to suffer even more, with their popular playlists experiencing a drop in weekly follower growth of over 0.3%. These findings are consistent across both the pandemic declaration and government restriction effects, suggesting that Spotify-curated playlists, unlike those curated by other stakeholders, maintained a favorable position in attracting listeners.

Estimated effects of changes in duration spent in places of residence (Figure 3) support that Spotify playlists curated by Spotify significantly benefited from users spending more time at home. However, contrary to the impacts of the pandemic declaration and government restrictions, the time spent at home (at mean) does not have any significant effect on popular playlists. On the other hand, it tended to have a positive effect on overall less popular playlists (Playlists that are not in top 5^{th} percentile). This shift in playlist followers patterns could suggest that listeners, with more time at home, explored beyond mainstream playlists to discover new or lesser-known content, possibly as a way to diversify their listening habits during an extended period of isolation.

From these findings, we infer that the pandemic did not reinforce the superstar effect but rather democratized playlist popularity by elevating follower growth for playlists in the mid-tail and long-tail. Spotify-curated playlists demonstrated notable resilience during the pandemic, while major labels and artists managed to alleviate some negative impacts more effectively than other curators, including professional and independent curators. This divergence may reflect the inherent advantage of being a well-resourced, platform-based curator, such as Spotify, which curates its own playlists and controls discovery algorithms. Unlike other curators, Spotify playlists might have benefited from the platform's recommendation algorithms and search visibility, which could have amplified their exposure and follower retention during a period when users were seeking more stable, reliable content.

These results suggest that, while major labels and artists showed adaptability or relatively less negative effects on their followers' growth, Spotify's playlists were outstandingly positioned to gain higher growth in user engagement during the pandemic. In other words, the pandemic reinforced the platform's resilience and influence within its own ecosystem.

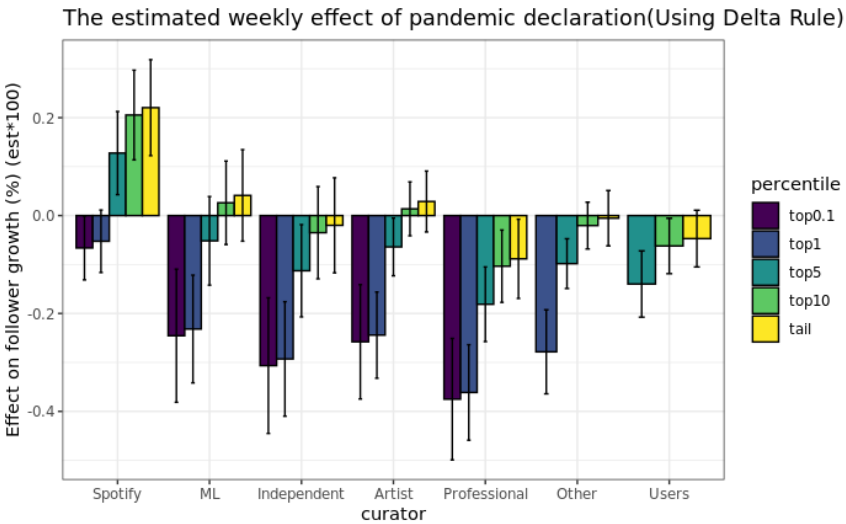

Figure 1: The estimated weekly effect of pandemic declaration

Notes: Total estimated effects from pandemic declaration by curator and popularity category, derived from the unit fixed-effects regression model. Standard errors are computed using the delta method by applying a first-order Taylor series approximation to obtain the variance of nonlinear combinations of estimated parameters.

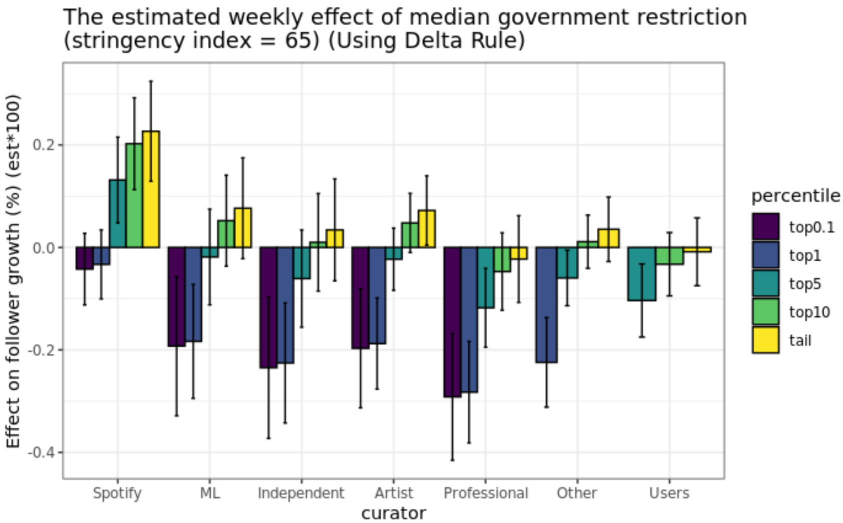

Figure 2: The estimated weekly effect of median government restriction
Notes: Total estimated effects from government restriction (with median of stringency index equivalent to 65) by curator and popularity category, derived from the unit fixed-effects regression model. Standard errors are computed using the delta method by applying a first-order Taylor series approximation to obtain the variance of nonlinear combinations of estimated parameters.

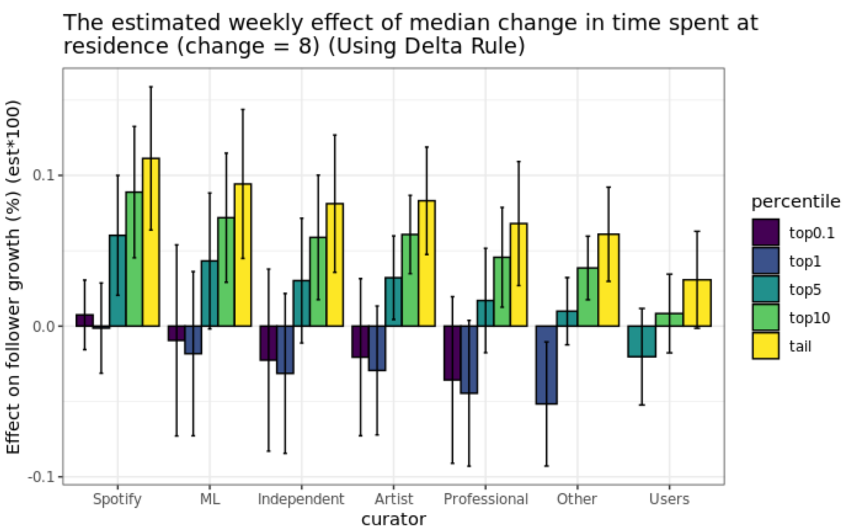

Figure 3: The estimated weekly effect of median change in time spent at home
Notes: Total estimated effects from time spent more at home (with median equivalent to 8) by curator and popularity category, derived from the unit fixed-effects regression model. Standard errors are computed using the delta method by applying a first-order Taylor series approximation to obtain the variance of nonlinear combinations of estimated parameters.

4.3.3 Effects on Content Producers

Our analysis explores whether playlists with a higher proportion of major label tracks demonstrated increased follower engagement during the pandemic. While we initially anticipated that playlists featuring more tracks from major labels would benefit from heightened appeal, the results suggest a mixed implication. Although we observe statistically significant ($p < .05$) positive effects from both the pandemic declaration and stricter government restrictions on follower growth for playlists with a greater major label share (Columns (2) and (4) in Table 4), these effects are economically small. Each 1% increase in major label track share is associated with only a marginal rise in follower counts, indicating that the role of major labels during this period, while detectable, may not have been substantial in shaping follower dynamics.

However, we observe significant ($p < .05$) negative effects associated with increased time spent at home (Column (6) in Table 4). This could indicate that, as users increased their time at home and had greater flexibility to explore less mainstream content, the appeal of playlists heavily featuring major label tracks may have diminished marginally. Users might have shifted attention toward a broader variety of content, potentially favoring independent or niche tracks that aligned more closely with their evolving daily routines or moods during an extended period of home confinement.

To further disentangle the effects of track popularity from label affiliation, we extended our model to include $AverageTrackShare$, a variable representing the average number of playlists on which each track appears on the platform (Table 5). By incorporating this measure, we can observe the impact of track popularity independently of major label affiliation. This additional variable indicates, on average, the number of playlists to which tracks from this list were added on Spotify. It is worth noting that there is no multicollinearity issue as the correlation between $MLShare$ and $AverageTrackShare$ is not high (i.e., 0.48). Once $AverageTrackShare$ is included, the effect of major label share becomes statistically insignificant ($p > 0.1$), while $AverageTrackShare$ itself is positively and significantly associated with follower growth. This result indicates that track popularity, rather than label branding, may have played a more critical role in follower engagement during the pandemic.

These findings suggest that, although major labels typically exert substantial influence in the music industry, their dominance was not evident on Spotify during the pandemic. With greater access to a wide range of content and more discretionary time, users appear to have responded more to the popularity and discoverability of individual tracks than to label affiliation. Playlists featuring widely included (and presumably popular) tracks attracted more followers, highlighting a shift toward content-driven engagement. In this context, the pandemic may have temporarily leveled the playing field, diminishing the branding advantage of major labels and emphasizing the appeal of high-rotation tracks regardless of their source.

Table 5: Excerpt of Estimated Results from a Unit Fixed Effects Model (Within Playlists) with An Addition of Track Popularity Proxy

Model:	CovidTime[1]	Stringency[1]	Residential[1]
MLShare	-0.0000	0.00000	0.00000
	(0.0000)	(0.00000)	(0.00001)
$Covid_t \times$ MLShare	0.0000	-0.00000	-0.00000***
	(0.0000)	(0.00000)	(0.00000)
AvgTrackShare	0.0010*	0.0010**	0.00130**
	(0.0004)	(0.0005)	(0.00055)
$Covid_t \times$ AvgTrackShare	0.0005***	0.00001***	0.00002***
	(0.0001)	(0.00000)	(0.00001)
Fit statistics			
Observations	1,917,624	1,917,624	1,917,624
R^2	0.0279	0.0279	0.0278
Within R^2	0.0024	0.0023	0.0022

1 Spotify is a based curator with superstar (top 0.1%) playlists.
Heteroskedasticity-robust standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5 Conclusion and Discussion

This study aimed to empirically examine how the COVID-19 pandemic affected Spotify's platform engagement by focusing on changes in playlist followers. Playlists are a key mechanism through which users discover and engage with music on streaming platforms. Changes in their follower counts can therefore reflect shifts in user behavior and the relative visibility of different stakeholders during the pandemic.

To structure our discussion, we revisit the study's four research questions, highlighting key findings and their implications. We then outline practical recommendations for industry stakeholders and conclude by reflecting on the study's limitations and directions for future research.

RQ 1: How did the number of followers for playlists change during the pandemic?

Although global subscriptions to music streaming platforms increased during the COVID-19 pandemic (RIAA, 2021), our results show no significant change in the average growth of playlist followers. This suggests that the rise in total platform usage did not translate uniformly into increased engagement with playlists within the platform.

The lack of overall change may reflect shifts in listening contexts. As prior research indicates, user engagement with music streaming is strongly influenced by daily routines, such as commuting or working environments (e.g., Sim et al., 2022; Denk et al., 2022). During the pandemic, while some new users may have joined the platform via home-based devices (e.g., smart TVs) (Spotify, 2021), others may have reduced their listening due to the loss of music-integrated routines (e.g., driving, gym use). This disconnect between continued subscription growth and stagnant playlist follower trends may reflect a form of behavioral inertia, a situation where users remain subscribed but reduce active engagement. This effect has been documented in other digital services as well (Rietveld & Schilling, 2020).

RQ 2: How did follower dynamics differ across playlists with varying levels of popularity during the pandemic?

Our findings reveal that the most-followed "superstar" playlists did not experience a significant increase in followers during the pandemic. Instead, playlists in the mid-tail and long-tail segments saw greater relative growth, particularly during periods when users spent more time at home. This pattern suggests that the pandemic did not amplify the existing superstar effect (Rosen, 1981; Elberse & Oberholzer-Gee, 2006); rather, it fostered broader playlist engagement across less prominent playlists, leading to a more balanced follower distribution.

This shift supports prior literature on digital content consumption, which highlights how lower discovery costs and increased time spent online can facilitate the exploration of diverse or niche content (Brynjolfsson et al., 2010). As discussed in our introduction, playlists play a central role in shaping listener behavior on streaming platforms by offering accessible, theme-based curation. During the pandemic, the extended time spent at home may have encouraged users to explore beyond highly visible content, resulting in increased engagement with mid-tail playlists, which are neither widely popular nor entirely obscure.

These findings indicate that user engagement during the pandemic became less concentrated on superstar playlists, highlighting the platform's potential to drive attention toward a broader range of content when listening behavior becomes more exploratory.

RQ 3: How did playlists curated by music streaming platforms, major labels, and independent curators differ in their resilience to changes in follower numbers during the pandemic?

Our findings show that playlists curated by Spotify demonstrated greater resilience and even achieved modest gains in follower counts during the pandemic. In contrast, playlists curated by major labels, professional tastemakers, and independent curators experienced significant declines in weekly follower growth. This pattern is consistent with prior research (e.g., Pachali & Datta, 2024; Aguiar & Waldfogel, 2021), which highlights the advantages of platform-curated content in terms of visibility, algorithmic promotion, and alignment with user preferences.

As discussed in the introduction, Spotify plays a dual role as both platform and curator, with its access to internal promotion mechanisms such as playlist featuring. Even after controlling for whether a playlist was featured on the platform, our results show that Spotify-curated playlists were less negatively affected by the pandemic and in some cases even gained followers. In contrast, major label-curated "superstar" playlists (i.e., top 0.1% by follower count) experienced declines of over 0.2% in weekly follower growth, which was equivalent to several thousand followers for a playlist with one million followers. Professional curators and independent labels, which typically have fewer resources and limited promotional visibility, saw even larger drops in follower engagement across popularity tiers. These findings suggest that curator types differed in their resilience to changes in follower numbers during the pandemic.

RQ 4: Did playlists featuring a higher proportion of tracks from major labels experience greater follower growth during the pandemic?

Our findings reveal that playlists with a higher share of tracks from major labels showed limited follower growth during the pandemic. While there were some statistically significant positive effects linked to government restrictions and platform activity, the effect sizes were very small, meaning that each 1% increase in major label track share corresponded to only marginal changes in weekly follower growth. This suggests that the presence of major label content alone did not strongly influence user engagement.

When we examined periods in which users spent more time at home, we observed a negative association between major label track share and follower growth. This pattern may reflect a shift in user preferences toward more diverse or independent content as users engaged more actively with the platform during extended home-based routines. As discussed in our introduction, playlists serve as a key interface between listeners and content producers, and the presence of well-known label content is often viewed as a signal of quality. However, our findings indicate that during the pandemic, this signal may have been less influential in shaping follower behavior.

Further analysis that included a proxy for track popularity, which is defined as how frequently tracks appeared across playlists, showed that this popularity measure, rather than label affiliation, better explained follower growth. Once track popularity was controlled for, the effect of major label share became statistically insignificant. This suggests that users responded more to recognizable or frequently featured tracks than to whether those tracks came from major labels.

Together, these results imply that playlists featuring a higher proportion of tracks from major labels did not experience greater follower growth during the pandemic. Instead, follower growth was more strongly associated with the inclusion of popular tracks, regardless of label affiliation.

Empirical Implications

Our findings have several implications for platform managers and content producers, particularly in navigating user engagement during periods of restricted mobility and changing routines from government restrictions.

First, the observed increase in follower growth among mid-tail and long-tail playlists, particularly when users spent more time at home, implies that listeners became more exploratory when their usual routines were changed. This pattern supports earlier work on how digital platforms with low discovery costs can enable broader content engagement (Brynjolfsson et al., 2010). For streaming platforms like Spotify, the growth in follower counts for mid-tail and long-tail playlists during periods of reduced mobility suggests that listeners were more willing to explore beyond the most-followed playlists. Rather than focusing solely on already-dominant playlists, platforms could use this insight to adjust their recommendation algorithms, or featured categories to surface mid-tier content that matches emerging listening routines, such as playlists for working from home, relaxation, or daily rituals. Doing so during periods of heightened residential time or strict policy restrictions may help retain user interest and foster deeper engagement, without depending entirely on superstar playlists whose visibility is already saturated.

For other content curators, our findings suggest that relying solely on flagship playlists or label-driven branding may be less effective during these periods. As users shift their attention based on changing contexts (e.g., more time at home), curators may benefit from diversifying the types of playlists they maintain, including more thematic, mood-based, or situational collections that resonate with listeners' daily activities. Additionally, rather than focusing only on playlist ownership, curators should aim to increase track-level presence across multiple playlists, as our results show that track popularity was a stronger driver of follower growth than label affiliation alone.

For track producers, including artists, independent labels, and major record companies, these results highlight the importance of widespread track inclusion across diverse playlists. Visibility was more strongly associated with track presence than with brand cues, suggesting that investing in track-level distribution strategies across playlists of different sizes and curators can increase exposure. Especially during periods of disrupted routines, maximizing reach through broader playlist placement may offer better engagement outcomes than relying on brand reputation or single high-profile placements.

Limitations and Future Research

This study opens up several avenues for future research that could address some limitations in our analysis. While we focused on a 49-week period to capture immediate pandemic effects, an extended timeframe would allow researchers to observe whether changes in playlist engagement persisted, diminished, or transformed as restrictions evolved or lifted. Future research could extend the analysis to cover post-pandemic recovery periods or subsequent waves of restrictions to evaluate whether shifts in follower behavior persisted or returned to pre-pandemic patterns. It is also possible that changes in listening behavior during this period were driven in part by a shift in attention from music playlists to other content formats, such as podcasts, which gained traction during the pandemic. Future research could examine whether rising podcast consumption contributed to flat or declining playlist follower growth, providing a fuller picture of how streaming preferences evolved under changing daily routines.

Second, although we focus on global playlists, this approach limits our ability to examine geographic variation in country-level user engagement. Because our data do not include country-level playlist identifiers, we rely on weighted indices of government restrictions and residential mobility. While this provides an indirect way to account for international variation, future research could benefit from more granular data that allows for regional comparisons. Country-specific studies could examine how national policies, cultural preferences, or local promotion strategies influence playlist engagement.

Third, our sample is restricted to playlists that existed before the pandemic declaration. While this choice allows us to track how established playlists responded to pandemic-related variations, it excludes newly launched playlists that may have been explicitly designed to meet emerging user needs, such as playlists for working from home, relaxation, or virtual gatherings. Future work could incorporate these newer playlists to understand content innovation and curation strategies during these periods.

Additionally, future research could explore how genre, mood, or activity-based themes influenced follower engagement independently of curator type or popularity tier. For example, playlists centered on emotional or motivational themes may have resonated more strongly with listeners navigating prolonged periods of isolation. Similarly, the role of personalized (algorithmically generated or user-specific) playlists deserves further attention, as such formats may engage users differently than public, platform-curated lists, particularly in the context of reduced physical mobility and increased screen time. Researchers might also consider experimental or simulation-based approaches to construct counterfactual scenarios, e.g., what platform engagement via playlists might have looked like without the pandemic. These designs could provide richer causal insights into how external shocks interact with platform dynamics and user behavior, beyond what observational data alone can reveal.

Lastly, future research could explore revenue-related impacts more directly, potentially focusing on how changes in engagement influence revenue distribution across labels and artists. Since revenue allocation on streaming platforms is often complex and not always transparent, examining metrics that are closely linked to artist and label income would enrich the understanding of how engagement trends during disruptions may translate into financial outcomes. Such research could ultimately guide artists, labels, and streaming platforms in aligning their strategies with user preferences and preparing for revenue fluctuations in times of restricted mobility and changing routines.

References

Aguiar, L., & Waldfogel, J. (2021). Platforms, power, and promotion: Evidence from Spotify playlists. *The Journal of Industrial Economics*, *69*(3), 653–691.

Aguiar, L., Waldfogel, J., & Waldfogel, S. (2021). Playlisting favorites: Measuring platform bias in the music industry. *International Journal of Industrial Organization*, *78*, 102765.

Boughanmi, K., & Ansari, A. (2021). Dynamics of musical success: A machine learning approach for multimedia data fusion. *Journal of Marketing Research*, *58*(6), 1034–1057.

Brynjolfsson, E., Hu, Y., & Simester, D. (2011). Goodbye Pareto Principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science*, *57*(8), 1373–1386.

Brynjolfsson, E., Hu, Y., & Smith, M. D. (2010). Research commentary—Long tails vs. superstars: The effect of information technology on product variety and sales concentration patterns. *Information Systems Research*, *21*(4), 736–747.

Cleeren, K., Dekimpe, M. G., & van Heerde, H. J. (2017). Marketing research on product-harm crises: A review, managerial implications, and an agenda for future research. *Journal of the Academy of Marketing Science*, *45*(5), 593–615.

Das, G., Jain, S. P., Maheswaran, D., Slotegraaf, R. J., & Srinivasan, R. (2021). Pandemics and marketing: Insights, impacts, and research opportunities. *Journal of the Academy of Marketing Science*, 1–20.

Datta, H., Knox, G., & Bronnenberg, B. J. (2018). Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Science*. https://pubsonline.informs.org/doi/abs/10.1287/mksc.2017.1051

Denk, J., Burmester, A., Kandziora, M., & Clement, M. (2022). The impact of COVID-19 on music consumption and music spending. *PLOS ONE*, *17*(5), e0267640. https://doi.org/10.1371/journal.pone.0267640

Elberse, A. (2008). Should you invest in the long tail? *Harvard Business Review*, *86*(7/8), 88.

Elberse, A., & Oberholzer-Gee, F. (2006). Superstars and underdogs: An examination of the long tail phenomenon in video sales. Citeseer.

Khamitov, M., Grégoire, Y., & Suri, A. (2020). A systematic review of brand transgression, service failure recovery and product-harm crisis: Integration and guiding insights. *Journal of the Academy of Marketing Science*, *48*(3), 519–542.

Knox, G., & Datta, H. (n.d.). Streaming services and the homogenization of music consumption. *Pure.Uvt.Nl*. https://pure.uvt.nl/ws/portalfiles/portal/39872868/streamagg_public.pdf

Kumar, A., Smith, M. D., & Telang, R. (2014). Information discovery and the long tail of motion picture content. *The Mississippi Quarterly*, *38*(4), 1057–1078.

Mu, J., Thomas, E., Qi, J., & Tan, Y. (2018). Online group influence and digital product consumption. *Journal of the Academy of Marketing Science*, *46*(5), 921–947.

Pachali, M. J., & Datta, H. (2025). What drives demand for playlists on Spotify? *Marketing Science*, *44*(1), 54–64.

Panico, C., & Cennamo, C. (2022). User preferences and strategic interactions in platform ecosystems. *Strategic Management Journal*, *43*(3), 507–529.

Papies, D., Ebbes, P., & Feit, E. M. (2022). Endogeneity and causal inference in marketing. https://doi.org/10.2139/ssrn.4091717

Papies, D., & van Heerde, H. J. (2017). The dynamic interplay between recorded music and live concerts: The role of piracy, unbundling, and artist characteristics. *Journal of Marketing*, *81*(4), 67–87.

Rietveld, J., & Schilling, M. A. (2021). Platform competition: A systematic and interdisciplinary review of the literature. *Journal of Management*, *47*(6), 1528–1563.

Rietveld, J., Schilling, M. A., & Bellavitis, C. (2019). Platform strategy: Managing ecosystem value through selective promotion of complements. *Organization Science*, *30*(6), 1232–1251.

Roggeveen, A. L., & Sethuraman, R. (2020). How the COVID-19 pandemic may change the world of retailing. *Journal of Retailing*, *96*(2), 169.

Rosen, S. (1981). The economics of superstars. *The American Economic Review*, *71*(5), 845–858.

Sim, J., Cho, D., Hwang, Y., & Telang, R. (2022). Frontiers: Virus shook the streaming star: Estimating the COVID-19 impact on music consumption. *Marketing Science*, *41*(1), 19–32.

Smith, M. D., & Telang, R. (2016). *Streaming, sharing, stealing: Big data and the future of entertainment*. MIT Press.

Yeung, T. Y.-C. (2020). Did the COVID-19 pandemic trigger nostalgia? Evidence of music consumption on Spotify. https://doi.org/10.2139/ssrn.3678606