Four Essays on Behavioral Pricing

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences,
International Affairs and Computer Science,
to obtain the title of
Doctor of Philosophy in Management

submitted by

Gianluca Scheidegger

from

Schaffhausen

Approved on the application of

Prof. Dr. Thomas Rudolph

and

Prof. Dr. Christian Hildebrand

Dissertation no. 5143

Difo-Druck GmbH, Untersiemau 2021

The University of St.Gallen, School of Management, Economics, Law, Social Sciences, International Affairs and Computer Science, hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, May 18, 2021

The President:

Prof. Dr. Bernhard Ehrenzeller

Acknowledgements

Throughout the writing of this dissertation, I have received tremendous support and assistance from my supervisor, coach, fellow academics, colleagues, family, and friends. I want to dedicate this section of my dissertation to thanking all these people.

Firstly, I would like to thank my supervisor and employer *Professor Thomas Rudolph*. With his excellent guidance and invaluable expertise, he empowered me to find practice-relevant research questions. Under his supervision, I was able to sharpen my skills and grow as a researcher. I would like to acknowledge my coach and mentor *Dr. Marc Linzmajer* for his enduring belief in my academic abilities beginning with my master's thesis. It was a great pleasure learning from him and collaborating with him on most of my research projects. *Professor Christian Hildebrand* helped me to improve my methodological skills and clarify my research questions. His PhD courses further fueled my enthusiasm for quantitative research.

My colleagues and former colleagues *Elias Barth, Dr. Melanie Basset, Professor Johannes Bauer, Dr. Severin Bischof, Andreas Hauschke, Professor Tim Böttger, Rolf Bottlang, Dr. Kristina Kleinlercher, Benjamin Klink, Nora Kralle, Barbara Langenegger, Sandra Lee, Tim Lersch, Professor Liane Nagengast, Kathrin Neumüller, Dr. Frauke Nitsch, Friederike Schlickenrieder*, *Jlona Stutz* and *Martina Tödtling* at the Institute of Retail Management made working and writing this dissertation enjoyable. Thank you for all the insightful and inspiring discussions, coffee breaks, lunches, excursions, gym breaks and after-work drinks. I am grateful to count many of you among my close friends.

I would like to thank the *Swiss National Science Foundation*, which supported me with a generous scholarship that made me financially independent during the last year of my PhD studies and permitted me to dedicate my time exclusively to research. For the duration of the scholarship, I was fortunate enough to spend time as a visiting researcher at HEC Paris. I would like to express my gratitude to *HEC Paris* and *Professor Marc Vanhuele's* great hospitality. At the same time, I am thankful to *Professor Priya Raghubir* for her belief in the relevance of my research and invitation to conduct a research visit at New York University Stern School of Business.

In addition, I want to profoundly thank my partner *Irina Blum* for her unconditional support, proofreading, and fruitful discussions along this 3.5-year journey. I am grateful to my family, including my brother *Davide Scheidegger* and my parents *Maria and Marco Scheidegger*, whose advice and encouragement have guided me throughout my whole life. Finally, I would like to thank all my friends because of whom I was always able to maintain a healthy work-life balance despite the heavy workload involved in writing this dissertation.

Winterthur, January 2021 *Gianluca Scheidegger*

Abstract

Behavioral pricing is the study of how consumers perceive and process price information, how they react to price changes, and how they use price information for their judgments and decisions. In the three main research areas of behavioral pricing, namely (1) effects of background variables, (2) processing fluency, and (3) mental accounting, emphasis is placed on psychological processes that help to better explain consumers' pricing-related behavior. In doing so, behavioral pricing is able to address shortcomings in traditional pricing models by accounting for the consumer perspective and considering the bounded rationality of people.

Using a customer-centric approach, the four essays in this dissertation examine consumer behavior considering recent developments in pricing. The **first essay** focuses on dynamic pricing in retailing and how different practices influence perceptions of value for money; the **second essay** addresses the question of optimal discount strategies in times of increasing price transparency; the **third essay** analyzes consumers' behavioral reactions to payments with fantasy currencies; and, finally, the **fourth essay** introduces and investigates discounted gift cards as an alternative form of price discount to consider in the pricing literature. Through these analyses, this dissertation shows how versatile and powerful behavioral pricing research is in understanding pricing-related consumer behavior and offers important implications for research and practice.

Zusammenfassung

Die Behavioral Pricing-Forschung untersucht, wie Konsumenten Preisinformationen wahrnehmen, verarbeiten und darauf reagieren. Zur besseren Erklärung des Preisverhaltens von Konsumenten ergänzt der verhaltenswissenschaftliche Fokus die neo-klassische Preistheorie durch die Integration psychologischer Theorien, Konzepte und Methoden. Das Forschungsfeld des Behavioral Pricing lässt sich darauf aufbauend in drei Bereiche unterteilen: (1) Den Einfluss von Kontextvariablen auf die Preiswahrnehmung, (2) die Informationsverarbeitung der Preisinformationen sowie (3) die mentale Buchführung. Die vorliegende Dissertation greift aktuelle Fragestellungen dieser drei Kernbereiche in vier Essays auf.

Vor dem Hintergrund der Digitalisierung thematisiert der **erste Essay** die dynamische Preisgestaltung im Einzelhandel und befasst sich mit der zentralen Frage, wie unterschiedliche Preisstrategien die Preisfairnesswahrnehmung von Konsumenten beeinflussen. Darauf aufbauend widmet sich der **zweite Essay** der spezifischeren Frage nach der optimalen Promotionsstrategie in Zeiten zunehmender Preistransparenz. Der **dritte Essay** untersucht, wie der Kontext der Preisdarstellung durch Phantasiewährungen die Kaufabsichten von Konsumenten beeinflusst. Abschliessend stellt der **vierte Essay** rabattierte Geschenkkarten als eine alternative Form des Preisnachlasses vor und analysiert, wie sich die Kostenwahrnehmung der Konsumenten beim Gebrauch dieser Geschenkkarten verändert. Zusammenfassend fördert diese Dissertation das Verständnis des Preisverhaltens von Konsumenten und liefert dadurch wichtige Implikationen für die verhaltenswissenschaftlich orientierte Preisforschung sowie die Praxis.

Table of Contents

Abstract ..... **III**
Zusammenfassung ..... **IV**

A. DISSERTATION OVERVIEW **1**
1. Introduction 2
2. Research Strategy 7
3. Synthesis 13

B. ESSAY I **19**
Rudolph, T., Scheidegger, G., Barth, E., and Linzmajer M. (published). The Dose Makes the Poison: Dynamic Pricing Strategies and Their Influence on Consumers. *Marketing Review St.Gallen.*

C. ESSAY II **39**
Scheidegger, G., Linzmajer, M., and Rudolph, T. (published). Price Discount Strategies in Times of Increasing Price Transparency: How Price Consciousness and Price Comparison Moderate the Effect of Discount Strategy on Store Price Image. *Die Unternehmung: Swiss Journal of Business Research and Practice.*

D. ESSAY III **65**
Scheidegger, G. (submitted). "35 Candy for a T-Shirt?": How a Currency's Dissimilarity to Money Decreases Purchase Intentions. *Psychology & Marketing*.

E. ESSAY IV **85**
Scheidegger, G., Linzmajer, M., Rudolph, T., Raghubir, P., and Bischof, S. (submitted). Pay Less, Spend More: Consumers' Mental Accounting for Discounted Gift Cards. *Journal of Marketing Research.*

F. CURRICULUM VITAE **113**

List of Figures

Figure A-1. Comparison of profit drivers 3
Figure A-2. Number of behavioral pricing publications and citations per year 5
Figure A-3. Synthesis 13
Figure B-1. Limitations of relative standard deviation as a measure for price fluctuation....25
Figure B-2. Dynamic pricing strategy clusters 27
Figure B-3. Mean fluctuation differences 28
Figure B-4. Average value for money ratings by pricing strategy....30
Figure B-5. Dynamic pricing strategy classification....34
Figure C-1. Number of promotions per week 45
Figure C-2. Mean discount depth development of EDLP and Hi-Lo retailers 46
Figure C-3. Conceptual diagram of the hypothesized moderated moderation model 48
Figure C-4. Two products across the 4 different price discount scenarios 50
Figure C-5. Store price image values 52
Figure C-6. Moderated moderation model....53
Figure D-1. Semantic and perceived money similarity....72
Figure D-2. Stimuli used for all three currency conversion scenarios in Study 2 74
Figure D-3. Path diagram 75
Figure D-4. Path diagram 77
Figure D-5. Hierarchical structure of concepts in WordNet 84
Figure E-1. Hypothesized relationship 94
Figure E-2. Exemplary payment depreciation 94
Figure E-3. Distribution of values across all scenarios grouped by discount type 97
Figure E-4. Distribution of values across all scenarios grouped by gift card type 100
Figure E-5. Distribution of values across all scenarios grouped by DGC face values 103
Figure E-6. Simple slope analysis 105

List of Tables

Table A-1. Dissertation overview and methodology 7
Table A-2. Exemplary profitability comparison 15
Table B-1. Four strategies for the same product “LEGO Technic – Mack Anthem” 32
Table B-2. PFM and PFF Ranges 35
Table C-1. Moderated moderation summary 54
Table D-1. WUP score calculations 84
Table E-1. Transparency levels of different payment mechanisms 93
Table E-2. Ten most popular gift card face values on cardpool.com 101

A. DISSERTATION OVERVIEW

1. Introduction

This introductory chapter briefly describes current pricing-related challenges in retailing. In addition, the advantages of behavioral pricing over traditional pricing models are discussed. In four essays, this dissertation addresses the identified challenges from a behavioral pricing perspective.

1.1. Pricing and Profitability in Retailing

"*The fastest and most effective way for a company to realize its maximum profit is to get its pricing right."*

(Marn & Rosiello, 1992, p. 84).

Global expansion and continuous growth of stock-keeping-units have drastically increased the complexity and operating costs of retailers in recent years (Dawson, 2010; Fisher et al., 2017). At the same time, sales growth is stagnating for many brick-and-mortar retailers. In store-based retailing, sales are expected to grow with a compound average growth rate of merely 1.1% (Switzerland), 2.1% (Germany), and 2.3% (Austria) between 2019 and 2024 in the DACH region (Euromonitor, 2020c, 2020b, 2020a).[1] Consequently, maintaining profitability has become a major concern for retail managers (Bolton et al., 2010; Fisher et al., 2017). Grocery retailers in particular operate with thin margins of approximately 1% of net sales (Bolton et al., 2010; Simon et al., 2010).

Costs, volume, and price are the main drivers of profitability (Marn & Rosiello, 1992; Simon, 2015). First, retailers only have limited possibilities to reduce costs and gain higher profitability. Most retailers will already have optimized their processes in the past, leaving limited room for improvement, while additional cost reductions require substantial investments in new technology (Simon et al., 2010). Furthermore, cost savings are mostly passed directly to customers through the reduction of prices (Simon et al., 2010).

Secondly, the Western retail market is saturated; thus, to increase the sales volume, retailers need to gain additional market shares (Simon et al., 2010). Fierce competition for market shares has resulted in aggressive price wars with large price reductions (Heil & Helsen, 2001; Kenning, 2011; Simon et al., 2010). Price wars have made consumers accustomed to frequent discounts, resulting in greater price sensitivity and less loyalty (Kenning, 2011; van Heerde et al., 2008). Retailers therefore find themselves stuck in the so-called "pro-

[1] Effects of the COVID-19 pandemic have not been considered in these estimations.

motion-trap" as they increasingly discount their products to appeal to increasingly price-sensitive customers (Bolton et al., 2010; Kenning, 2011; Sebastian, 2013; van Heerde et al., 2008). According to Bolton et al. (2010), retailers generate about 20% of their sales with price promotions and spend about 80% of the week managing these promotions. As such, retailers' efforts to decrease costs or increase volumes do not necessarily result in higher profits due to saturated markets with small growth rates (Euromonitor, 2020b, 2020c, 2020a; Simon et al., 2010), price wars (Sebastian, 2013; van Heerde et al., 2008), and limited cost optimization potential (Simon et al., 2010).

The third main driver of profitability is price. In contrast to volume changes, price changes have an immediate effect on profits. As illustrated in Figure A-1, even a small price change of 1% can create significant additional profit of 11.10%, more than any other driver. Simon et al. (2010) estimated that some retailers may even be able to increase their profit by 60-70% with a price increase of 1%. This disproportionally strong impact on profitability makes pricing one of the most essential tasks of retail managers.

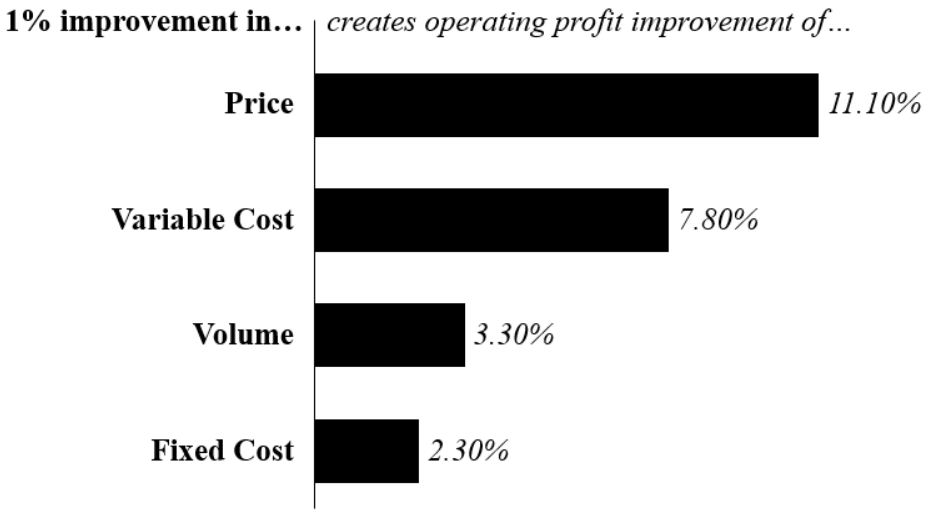


Figure A-1. Comparison of profit drivers. For example, 1% improvement of variable cost creates operating profit improvement of 7.80%. Adapted from Marn and Rosiello (1992).

The importance of pricing for profitability is undisputed, yet optimizing price setting has presented challenges in research and practice alike. Although microeconomic price optimization models have been around for decades, they are not widely used by retailers (Simon et al., 2010). Finding the optimal price using these models usually requires complex calculations, detailed knowledge of competitors, consumers' demand functions for each product, or cross-price-elasticities between complementary products and substitutes (Frank, 2010). Since retailers often lack this information and regularly set prices for several thousand products, these classical pricing models are not effective. In addition, most microeconomic pricing

models rely on the assumption that consumers are fully informed, rational decision-makers who aim to maximize their utility (Frank, 2010; Liu & Soman, 2008). However, this assumption has long been disputed by behavioral scientists who try to generate actionable insights for research and practice by studying actual and not idealized consumer behavior (e.g., Ariely, 2010; Kahneman, 2011; Thaler & Sunstein, 2009). In fact, consumers tend to make satisfying rather than optimizing choices (Liu & Soman, 2008).

The potential of behavioral research in helping retailers solve profitability challenges through effective pricing decisions is discussed in the following section and in each of the four dissertation essays.

1.2. Advantages of Behavioral Pricing

"Price is undoubtedly one of the most important market variables. Given the human complexity in psychological processes and limitation in cognitive capabilities, it is not surprising to see that traditional economic theory and normative choice models often fall short in explaining consumer choice and consumption."

(Liu & Soman, 2008, p. 676)

Behavioral pricing research has grown in relevance since 1990. The number of publications as well as citations has steadily increased almost every year. This development is illustrated in Figure A-2. Today, behavioral pricing is as relevant as ever before.[2]

There are multiple reasons why behavioral pricing has become so popular. Firstly, it addresses shortcomings in traditional pricing models by accounting for the consumer perspective and considering the bounded rationality of people (Liu & Soman, 2008). Academics and managers were able to broaden their understanding of consumers' actual purchase behavior by deviating from traditional rationality assumptions (Koschate-Fischer & Wüllner, 2017). Secondly, it combines findings from different research areas. Researchers from the fields of psychology (e.g., Alter & Oppenheimer, 2008; Raghubir & Srivastava, 2008), economics (e.g., Shafir & Thaler, 2006; Soetevent, 2011), and marketing (e.g., Cheng & Cryder, 2018; Prelec & Loewenstein, 1998) contribute to predictions of consumer reactions to price-related changes. Thirdly, behavioral pricing findings are highly practice-relevant as they try to solve businesses' profitability and pricing issues. Finally, research in behavioral pricing focuses on the way prices are presented rather than the setting of the price itself (Liu & Soman, 2008); this makes the implications of the research generally easy to implement.

[2] Unsurprisingly, the well-known Journal of the Association for Consumer Research (JACR) has devoted a 2021 special issue to behavioral pricing (JACR, 2020).

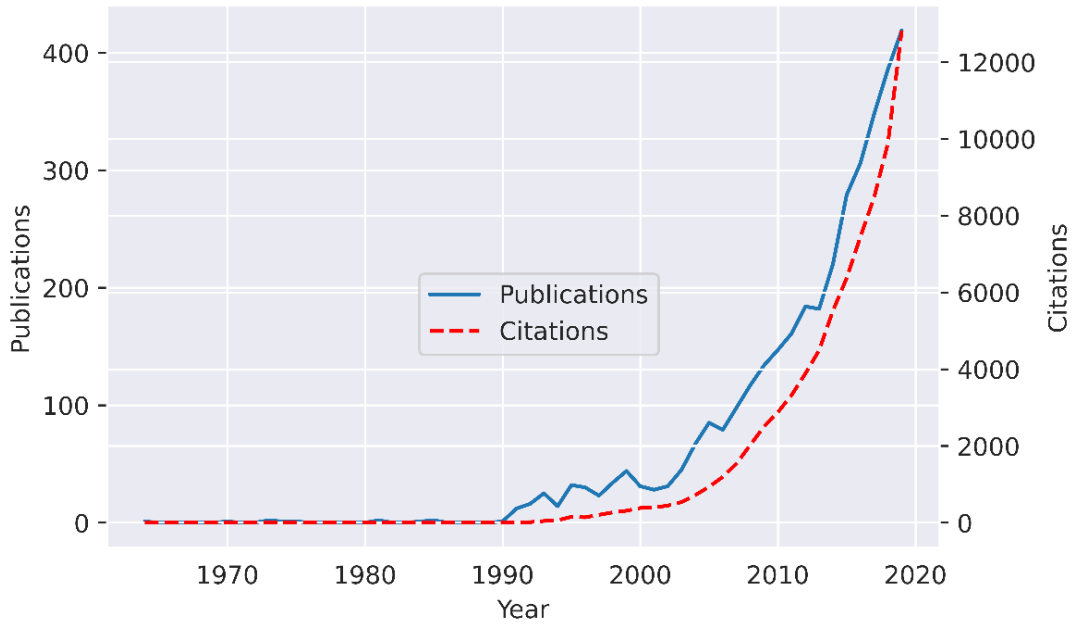


Figure A-2. Number of behavioral pricing publications and citations per year from 1964 to 2019. Based on a Web of Science keyword search for "behavioral pricing."

Consumers' price-related judgements and decisions are influenced by numerous factors. Researchers have categorized these factors into three main areas of behavioral pricing research: (1) effects of background variables, (2) processing fluency, and (3) mental accounting (Liu & Soman, 2008). The first area, effects of background variables, focuses on how consumers evaluate product or service attributes in the presence and absence of context (Nowlis & Simonson, 1997). Some attributes, such as brand quality, are context-independent and can be evaluated reliably in the absence of alternatives (Nowlis & Simonson, 1997). Others, such as price information, are highly context-dependent (Nowlis & Simonson, 1997). Consumers rely heavily on price and product comparisons, reference points (e.g., manufacturer's suggested retail price), and their own experiences to evaluate prices (Liu & Soman, 2008). Thus, adapting the context in which the price information is presented without changing the price itself influences consumer preferences (Nowlis & Simonson, 1997). For example, Ferrero, an Italian manufacturer of confectionary products, famously calls its Duplo chocolate bar "the world's longest praline." Pralines have a more favorable quality image than chocolate bars; thus, association with a praline rather than a chocolate bar, which is reinforced by placing the Duplo bar close to the pralines on shelves, can increase consumers' interest and willingness to pay for the product (Strelow et al., 2020).

The second main area of behavioral pricing is processing fluency. Researchers in this area investigate the conscious and unconscious perceptions, encoding, and processing of information (Liu & Soman, 2008). Consumers try to minimize difficult cognitive activity during product evaluations (Liu & Soman, 2008; Novemsky et al., 2007). In this context, processing

fluency refers to ease of information processing (Schwarz, 2004) that is dependent on an information's individual presentation (e.g., font, color, position or size; Coulter & Coulter, 2005, 2010). Changing this presentation to support more fluent information processing leads to positive consumer reactions (Liu & Soman, 2008). On the contrary, communicating price or product information in a less fluent format, for example with a difficult to read font ('*CHF 399*' instead of 'CHF399') has been proven to defer purchase choice (Novemsky et al., 2007).

Mental accounting is the third and last main area of behavioral pricing. It has been described as the process of consumers' financial decision-making, its subsequent evaluation, and the categorizing of financial expenditures into different cognitive accounts (Thaler, 1985). People treat funds in their mental accounts differently depending on several factors: the time difference between payment and consumption (Gourville & Soman, 1998; Shafir & Thaler, 2006), the form of payment (Chatterjee & Rose, 2012; Khouja et al., 2011; Raghubir & Srivastava, 2008; Soman, 2001, 2003; White, 2008), and the categorization of payments (e.g., Prelec & Loewenstein, 1998; Thaler et al., 2000). Broadly speaking, consumers categorize their assets into two accounts: (1) current income and (2) current wealth account (Shefrin & Thaler, 1988). Whereas the money in the current wealth account is handled conscientiously, consumers are strongly tempted to spend money assigned to the current income account (Shefrin & Thaler, 1988). This behavior violates the assumption that all money is interchangeable independent of its form and origin and results in financial decisions that seem counterintuitive from an economic perspective (Thaler et al., 2000). For example, consumers tend to classify unexpected price discounts as "windfall gains" that they assign to their current income account. Then, they are more likely to buy products that they would usually not buy because of these "gains" (Milkman & Beshears, 2009).

In summary, behavioral pricing research shows that consumer behavior strongly depends on people's individual price information processing. At the same time, various factors such as the form of payment, lack of context and fluency of the displayed information influence information processing. These influencing factors are constantly evolving: for example, new payment forms are being introduced (e.g. discounted gift cards or fantasy currencies), technological advances allow for dynamic price changes, and consumers have constant access to competitors' price comparison websites on their mobile phones. These developments open new avenues for behavioral pricing research and pose new opportunities and challenges for practice.

The next section discusses how this dissertation aims to contribute to all three behavioral pricing areas by addressing newly emerged research gaps and managerial problems in the light of recent developments.

2. Research Strategy

Table A-1. Dissertation overview and methodology.

	ESSAY I	ESSAY II	ESSAY III	ESSAY IV
TITLE	The Dose Makes the Poison: Dynamic Pricing Strategies and Their Influence on Consumers	Price Discount Strategies in Times of Increasing Price Transparency: How Price Consciousness and Price Comparison Moderate the Effect of Discount Strategy on Store Price Image	"35 Candy for a T-Shirt?": How a Currency's Dissimilarity to Money Decreases Purchase Intentions	Pay Less, Spend More: Consumers' Mental Accounting for Discounted Gift Cards
CO-AUTHORS	Thomas Rudolph, Elias Barth, Marc Linzmajer	Marc Linzmajer, Thomas Rudolph	–	Marc Linzmajer, Thomas Rudolph, Priya Raghubir, Severin Bischof
RESEARCH QUESTION	Which dynamic pricing strategies exist in the field, and how do they influence consumers' value-for-money perceptions?	How did price discount strategies evolve in recent years, and how do they influence consumers' store price image evaluations?	How do fantasy currencies influence consumers' purchase intentions?	How do discounted gift cards influence consumers' cost perceptions?
METHODS	Collection and analysis of field data	Collection and analysis of field data. Computer-based experiment	Computer-based experiments	Analysis of field data and computer-based experiments
DATA	3,044,625 price observations from 24,817 individual retailer-product-combinations and 105,469 retailer ratings	23,495 discount prices and 498 experiment participants	864 experiment participants	212 airline bookings, 1,744 experiment participants
PUBLICATION STATUS	Published in *Marketing Review St.Gallen*	Published in *Die Unternehmung: Swiss Journal of Business Research and Practice*	Submitted to *Psychology & Marketing*	Submitted to *Journal of Marketing Research* Presented at *ACR Conference 2020*

This dissertation seeks to advance theoretical and practical understanding within the three main pillars of behavioral pricing research, namely the effects of background variables (Essay I & II), processing fluency (Essay III), and mental accounting (Essay IV). All four essays start by identifying a research gap, generate hypotheses based on previous research, provide empirical evidence for these hypotheses, and deliver impactful implications for retailers. Table A-1 as well as Sections 2.1, 2.2, 2.3, and 2.4 provide (extended) summaries of the dissertation essays.

2.1. Summary of Essay I

Title: The Dose Makes the Poison: Dynamic Pricing Strategies and Their Influence on Consumers.

Research Problem: Technological advancements in price setting have enabled retailers to frequently adapt their prices at low costs. Dynamic pricing can help retailers to quickly react to changes in their business environment and optimize their margins. However, research as well as anecdotal evidence suggest that retailers should be cautious in using dynamic pricing. If a dynamic pricing tactic is perceived as unfair, it can have negative consequences for the retailer (e.g. negative word-of-mouth in newspapers). Even though consequences of dynamic pricing have been subject to research, little is known about different dynamic pricing strategies retailers use and how these strategies individually influence customer perceptions.

Research Goal: The goal of this essay is to empirically categorize different dynamic pricing strategies used by online and cross-channel retailers. We aim to generate valuable insights by analyzing the effects of different dynamic pricing strategies on consumers' price perceptions. Finally, we try to formulate recommendations on how dynamic pricing can be used successfully and without risk of consumer outrage.

Methodology: We collected real price data from a price comparison website over a period of 50 days. Based on our observations, we calculated different clusters of dynamic pricing strategies. We matched these identified dynamic pricing strategies with collected value for money ratings of each retailer to test how each strategy influences consumer ratings.

Results: We were able to classify four dynamic pricing strategies: Same Price Strategy (63% of retailers), Frequency Strategy (2%), Magnitude Strategy (11%), and Hybrid Strategy (23%). The analyses show that only the magnitude and not the frequency of price changes negatively influenced consumers' value for money ratings. Furthermore, pure online retailers adapted prices more frequently and with a higher magnitude than cross-channel retailers.

Contribution: The contributions of this essay are twofold. From a managerial perspective, we deliver a comprehensive overview of the current market situation regarding dynamic

pricing usage. Managers can use our thresholds as benchmarks to design a balanced dynamic pricing strategy that minimizes negative consumer response. From a theoretical perspective, we introduce two price fluctuation metrics to the literature that enable a differentiated classification of dynamic pricing strategies. The results offer a validation of empirical findings from previous experimental studies in the field.

2.2. Summary of Essay II

Title: Price Discount Strategies in Times of Increasing Price Transparency: How Price Consciousness and Price Comparison Moderate the Effect of Discount Strategy on Store Price Image.

Research Problem: Intensifying competition and greater numbers of price-sensitive customers have forced grocery retailers into a promotion-trap with numerous negative economic consequences. Although extant research has not been able to unequivocally confirm the hoped-for positive long-term effects of price discounts on important company metrics such as store price image, companies intensify their promotion activity. More specifically, it remains unclear how to balance the number of discounts and discount depth while increasing promotion activity in general. At the same time, consumers often use price comparison tools to search for the best offers online while at home or even in the store. This change in consumer behavior and a lack of clarity regarding the optimal discount strategy require further research.

Research Goal: Our first goal is to better understand current developments in retailers' discount strategies. Specifically, we aimed to observe how the number of product discounts and discount depth have evolved in recent years. Secondly, we wanted to determine whether the number of discounts or discount depth plays a larger role in consumers' formation of store price images. Thirdly, we sought to understand how consumers' price consciousness and price comparisons influence the relationship between discount strategy and store price image.

Methodology: Over a two-year time period, we collected the weekly price discount brochures of four major Swiss retailers to compile a large set of price discount data. We analyzed this field data to identify different developments in price discount strategies over the two-year period. In a laboratory experiment, we tested how these strategies and price comparisons influenced consumers' store price image perceptions.

Results: Swiss grocery retailers increased the number of discounts offered over two years. The number of discounted products had a significant positive effect on store price image. On the other hand, discount depth had no influence on store price image. These effects were dependent on consumers' price consciousness and their (non-)usage of a price comparison tool.

Contribution: From a managerial perspective, retailers in particular can profit from our findings when evaluating their own price discount strategies. We show which price discount factors influence the price image of a store and which do not. From a theoretical perspective, we contribute to the literature on discount strategies by accounting for new developments in consumer behavior (i.e., price comparisons).

2.3. Summary of Essay III

Title: "35 Candy for a T-Shirt?": How a Currency's Dissimilarity to Money Decreases Purchase Intentions.

Research Problem: Researchers in behavioral pricing mainly focus their studies on official currencies such as US dollars or euros, yet businesses such as game developers, retailers, and festival organizers generate substantial revenues with fantasy currencies. Due to the lack of research on fantasy currencies, it remains unclear how consumers alter their spending behavior when using such currencies.

Research Goal: Building on previous research in the field of payment transparency and processing fluency, we aim to predict consumer behavior in the use of fantasy currencies. To this end, we sought to find influential mediators that explain the underlying psychological processes of a purchase decision with fantasy currencies. These findings should result in actionable and easy-to-implement implications for practitioners and pave the way for further research on fantasy currencies.

Methodology: We tested our hypothesized effects in two experimental studies using real-world inspired purchase scenarios. In addition, we used WordNet – a lexical database – and an additional experimental study to predict how different fantasy currencies (e.g., Candy versus Gold) influence this psychological process.

Results: The calculated Wu-Palmer semantic money similarity based on WordNet was able to predict perceived similarity for five fantasy currencies. In a serial mediation, perceived dissimilarity to money led to a decrease in processing fluency that subsequently led to an increase in pain of payment. Purchase intentions decreased with a higher pain of payment.

Contribution: This essay contributes to behavioral pricing research by introducing and analyzing purchases with fantasy currencies. We derive two explanatory approaches from previous research and illustrate why only one – processing fluency – may be applicable in the context of fantasy currencies. Our managerial contribution is straightforward: retailers, game developers and event organizers should consider semantic money similarity when developing a new fantasy currency. Otherwise, they run the risk of reducing consumers' purchasing intentions.

2.4. Summary of Essay IV

Title: Pay Less, Spend More: Consumers' Mental Accounting for Discounted Gift Cards.

Research Problem: Aside from regular price discounts, firms have created discounted gift cards (DGCs) in order to attract increasingly deal-sensitive customers. Contrary to what their name might suggest, DGCs are less intended as something to purchase for others and are rather a self-gift for bargain hunters to be used at a future point in time. In comparison to cash, gift cards are a non-transparent payment type; this has considerable implications for consumers as they must first switch from cash to a gift card in order to obtain a price discount. In purchasing DGCs, consumers might ultimately spend more money than initially intended. Previous research has shown that payment mechanisms that temporally separate the payment (e.g., buying a gift card) and consumption (e.g., buying a product with the card) can lead to counterintuitive financial decision-making. More precisely, Gourville and Soman (1998) underlined that consumers tend to depreciate initial payments over time, rendering the costs less relevant at the time of consumption. Building upon these findings, we investigate this new discount type's effects on consumers' purchase decisions.

Research Goal: This research aims to shed light on the mental accounting process involved in the purchase of DGCs and to identify processes that influence consumers' reduced subjective costs associated with DGCs. These findings should help managers and service providers who seek a (possibly more effective) alternative to regular price discounts.

Methodology: In two lab experiments, we identified the main effect of DCGs, namely payment depreciation. Then, we systematically ruled out alternative explanations by comparing DGCs to related payment and discount methods. Actual booking data from an international airline helped to add external validity to the results from the lab studies. We provided practitioners with additional information about this new form of discount and their optimal design by testing out different DGC configurations (e.g. face values) in a fourth study.

Results: Consumers' subjective cost evaluations for DGC purchases were dependent on how long they waited to redeem the DGC. The longer they kept the DGC before redeeming it, the less they felt they were spending on the purchase. We were able to replicate this effect in the field by showing that consumers spent more on airline tickets the longer they kept a DGC compared to a control group with regular gift cards. Keeping nominal discounts constant, this cost depreciation effect of DGCs increased with the increasing face value of the DGC (e.g., $25 gift card for $5 versus $200 gift card for $180).

Contribution: From a theoretical perspective, this essay contributes to mental accounting literature by showing payment depreciation not only in the context of sunk costs but also

in regular product purchases based on partial rather than complete prepayment. Furthermore, we introduce a new payment mechanism and promotion type to the academic literature and differentiate it from regular promotion types to extend and combine publications on payment and promotion types. From a societal perspective, the result of this project should inform policymakers' awareness of non-transparent payment mechanisms and help consumers avoid overspending because of a systematic underestimation of costs. From a managerial perspective, this research aims to establish DGCs as an alternative to regular price promotions.

3. Synthesis

Figure A-3 summarizes the simplified main implications for academics and retailers that can be drawn from each of the four dissertation essays and how they affect consumers (behavioral effects) and retail businesses (bottom-line effects).

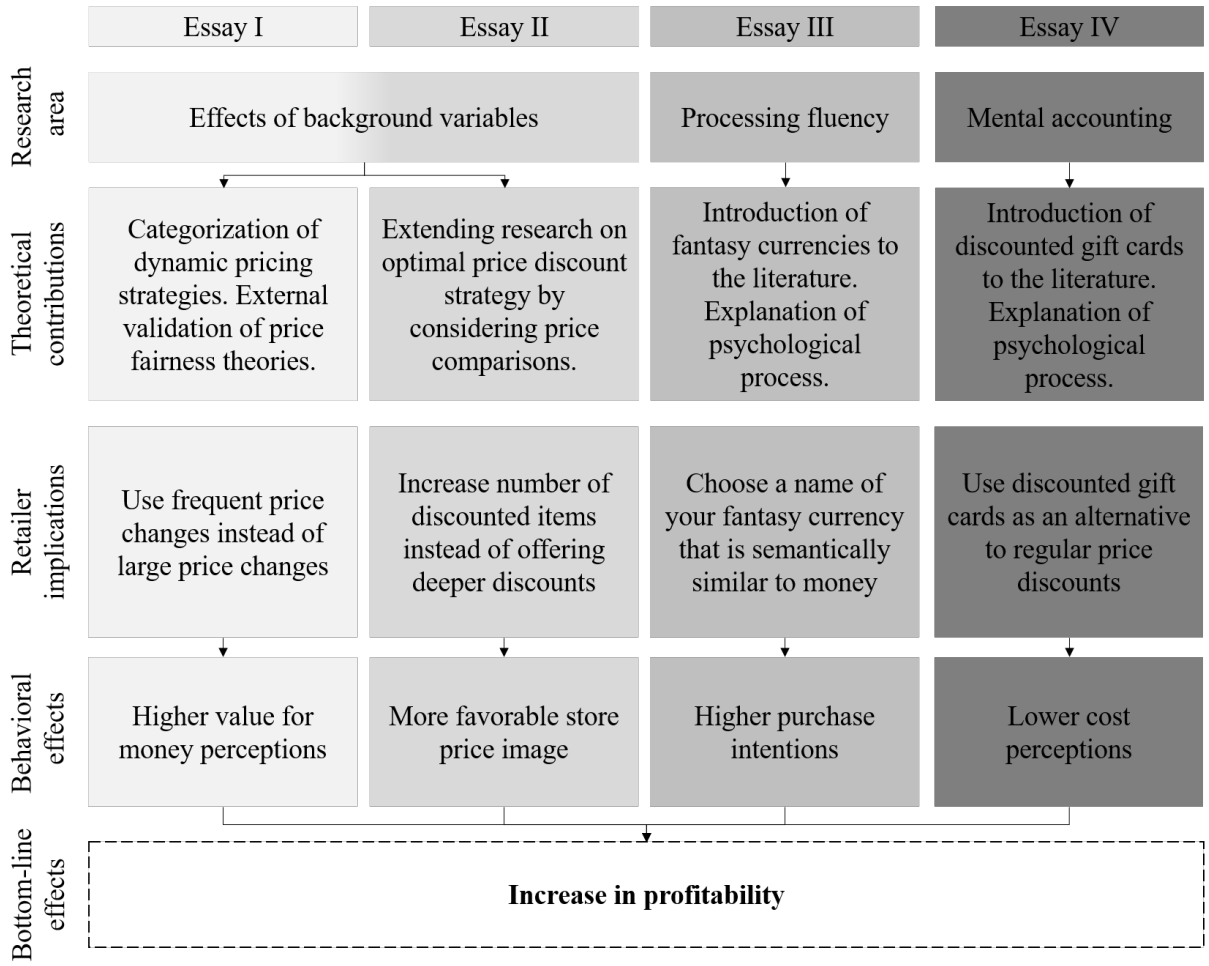


Figure A-3. Simplified theoretical contributions, retailer implications, and resulting behavioral and bottom-line effects for each essay.

Essay I analyzes how retailers can apply dynamic pricing to optimize margins and increase profitability. One key issue in using dynamic pricing is that consumers may perceive this practice as inherently unfair. However, our research shows that if only used moderately and below a certain price fluctuation threshold, price changes do not affect consumers' price perceptions. At the same time, frequent price changes seem to be more accepted than large price changes. Moreover, we provide detailed information on how retailers can evaluate their dynamic pricing intensity compared to competitors by using freely available information on price comparison websites. In addition, retailers can use the thresholds we provide to fine-

tune their dynamic pricing algorithms for higher consumer acceptance and thus more profitability in the long run.

Essay II addresses the important issue of price discount strategies. Previous research has demonstrated that store price image is one of the most important determinants of consumers' store choice. As such, maintaining a favorable store price image and becoming the consumers' retailer of choice is key to running a profitable retail business in a saturated market. We reveal that all analyzed retailers offered more discounts, and some even increased discount depth at the same time. However, our results indicated that only the number of discounted products and not the discount depth positively influenced store price image; this holds important implications for retailers because every price decrease significantly harms the profit margin. Offering deeper discounts may therefore diminish profits without necessarily improving store price image. Furthermore, we show that the positive effect of the number of discounted items on store price image is stronger among highly price-conscious customers and lower for customers with access to a price comparison tool; this implies that with increasing price transparency due to the emergence of price comparison tools, the positive effect of some discounting strategies on store price image may vanish.

Essay III highlights the phenomenon of fantasy currencies. Compared to the topics in Essay I and II, fantasy currencies are a highly understudied subject in marketing research. Some retailers, game developers, and event organizers already generate considerable revenues in the form of "Gems," "Candy," or "Coins." Nonetheless, it remains unclear how the act of purchasing products or services with such currencies is perceived by consumers. Based on our findings, we recommend that retailers use a fantasy currency with a name that is semantically similar to the concept of money. Customers generally dislike when price information is hard to process. For currencies with a high dissimilarity to money, processing fluency is low. Thus, consumers reduce their purchase intentions, producing a negative effect on profitability. Essay III describes how retailers planning to introduce a fantasy currency for their loyalty program, event, or online store can pretest the currency name to avoid negative behavioral effects. The WordNet database offers a free and simple method to calculate the semantic similarity between the desired currency name and money.

Essay IV provides evidence that discounted gift cards (DGCs) may be a cost-effective alternative to regular price discounts. Based on mental accounting, we illustrate that consumers' subjective costs are lowered when they pay with DGCs because they depreciate the costs of a DGC over time. The reduction of subjective costs is even higher among DGC users than among consumers redeeming a normal gift card or profiting from a regular and financially equivalent price discount. Regular price discounts usually start at 20% (for an example, see Essay II). We show that DGCs can reduce consumers' subjective costs when offering only a

10% discount on the gift card's face value. In one scenario, consumers bought a $200 gift card for $180. Later, they purchased a $300 laptop using this gift card. On average, they reported that it felt like they were spending $214 only. This reduction in cost perceptions would correspond to a price discount of 23.6%.[3] Achieving the same behavioral effects as a 23.6% price discount with a 6.7% discount[4] makes a DGC extremely attractive from a profitability perspective. Assuming that the laptop retailer has a profit margin of 30% on the laptop (see Table A-2), selling the laptop at its normal price would result in a profit of $90. When the retailer discounts the laptop by 23.6%, only $19.20 of profit remains (constituting a profit loss of 78.7%). Using a DGC of similar behavioral attractiveness results in a profit loss of 22.3% only, which is 3.5 times less compared to the regular discount.[5]

In addition, consumers do not redeem the full amount of gift cards. Undisclosed discussions with industry experts indicate that, on average, at least 9% of gift card values remain unredeemed. This unredeemed money may be accounted for as additional profit after the legal expiration period of the gift card. Accounting for this unredeemed value, our fictitious laptop retailer lost only 2.2%[6] of its profit due to the gift card discount (35.8 times less compared to the regular discount).

Table A-2. Exemplary profitability comparison between DGC and price discount of same behavioral attractiveness.

	No discount	**23.6% discount**	**6.7% discount**
Sales price	$300	$229.20	$280
Fixed costs	$210	$210	$210
Profit	$90	$19.20	$70
Profit loss	-	78.7%	22.2%

[3] $300 (laptop) - $20 (DGC discount) = $280. $1 - \frac{\$214}{\$280} = 23.6\%$

[4] 10% discount on the gift card purchase ($20) corresponds to 6.7% discount on the laptop purchase: $1 - \frac{\$280}{\$300} = 6.7\%$

[5] This is a very simplified calculation to illustrate the effectiveness of DGCs. Real profit margins may be considerably lower.

[6] Assuming 9% of the $200 gift card value remain unredeemed, the retailer receives an additional profit of $18. This results in a profit of $70 + $18 for the retailer: $1 - \frac{\$88}{\$90} = 2.2\%$.

References

Alter, A. L., & Oppenheimer, D. M. (2008). Easy on the mind, easy on the wallet: The roles of familiarity and processing fluency in valuation judgments. *Psychonomic Bulletin and Review, 15*(5), 985–990. https://doi.org/10.3758/PBR.15.5.985

Ariely, D. (2010). Predictably irrational. Harper Perennial: New York.

Bolton, R. N., Shankar, V., & Montoya, D. Y. (2010). Recent trends and emerging practices in retailer pricing. In M. Krafft & M. K. Mantrala (Eds.), Retailing in the 21st Century: Current and Future Trends (2nd ed., pp. 255–269). Springer: Heidelberg. https://doi.org/10.1007/3-540-28433-8_17

Chatterjee, P., & Rose, R. L. (2012). Do Payment Mechanisms Change the Way Consumers Perceive Products? *Journal of Consumer Research, 38*(6), 1129–1139. https://doi.org/10.1086/661730

Cheng, A., & Cryder, C. (2018). Double Mental Discounting: When a Single Price Promotion Feels Twice as Nice. *Journal of Marketing Research, 55*(2), 226–238. https://doi.org/10.1509/jmr.15.0559

Coulter, K. S., & Coulter, R. A. (2005). Size does matter: The effects of magnitude representation congruency on price perceptions and purchase likelihood. *Journal of Consumer Psychology, 15*(1), 64–76. https://doi.org/10.1207/s15327663jcp1501_9

Coulter, K. S., & Coulter, R. A. (2010). Small Sounds, Big Deals: Phonetic Symbolism Effects in Pricing. *Journal of Consumer Research, 37*(2), 315–328. https://doi.org/10.1086/651241

Dawson, J. (2010). GLOBAL TRENDS: Retail Trends in Europe. In M. Krafft & M. K. Mantrala (Eds.), Retailing in the 21st Century: Current and Future Trends (2nd ed., pp. 63–81). Springer.

Euromonitor. (2020a). Country Report: Retailing in Austria. https://www.portal.euromonitor.com/portal/analysis/tab

Euromonitor. (2020b). Country Report: Retailing in Germany. https://www.portal.euromonitor.com/portal/analysis/tab

Euromonitor. (2020c). Country Report: Retailing in Switzerland. https://www.portal.euromonitor.com/portal/analysis/tab

Fisher, M., Gaur, V., & Kleinberger, H. (2017). Curing the Addiction to Growth. *Harvard Business Review*, January-February.

Frank, R. H. (2010). Microeconomics and behavior (8th ed.). McGraw-Hill/Irwin: New York.

Gourville, J. T., & Soman, D. (1998). Payment Depreciation: the Behavioral Effects of Temporally Separating Payments From Consumption. *Journal of Consumer Research*, 25(2), 160–174. https://doi.org/10.1086/209533

Heil, O. P., & Helsen, K. (2001). Toward an understanding of price wars: Their nature and how they erupt. International *Journal of Research in Marketing*, 18(1–2), 83–98. https://doi.org/10.1016/S0167-8116(01)00033-7

JACR. (2020). Behavioral Pricing. https://www.journals.uchicago.edu/journals/jacr/forthcoming-6.1

Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux: New York.

Kenning, P. (2011). Preissenkungen Machen Kunden Zu Vagabunden. *Harvard Business Manager*.

Khouja, M., Pan, J., Ratchford, B. T., & Zhou, J. (2011). Analysis of free gift card program effectiveness. *Journal of Retailing, 87*(4), 444–461. https://doi.org/10.1016/J.JRETAI.2011.06.002

Koschate-Fischer, N., & Wüllner, K. (2017). New developments in behavioral pricing research. *Journal of Business Economics, 87*(6), 809–875. https://doi.org/10.1007/s11573-016-0839-z

Liu, M. W., & Soman, D. (2008). Behavioral Pricing. In C. Haugtvedt, P. Herr, & F. Kardes (Eds.), Handbook of Consumer Psychology (pp. 659–681). Taylor & Francis Group: London.

Marn, M. V, & Rosiello, R. L. (1992). Managing Price, Gaining Profit. *Harvard Business Review*, September-October, 84–94.

Milkman, K. L., & Beshears, J. (2009). Mental accounting and small windfalls: Evidence from an online grocer. Journal of Economic Behavior and Organization, 71(2), 384–394. https://doi.org/10.1016/j.jebo.2009.04.007

Novemsky, N., Dhar, R., Schwarz, N., & Simonson, I. (2007). Preference Fluency in Choice. *Journal of Marketing Research, 44*(August), 347–356.

Nowlis, S. M., & Simonson, I. (1997). Attribute-Task Compatibility as a Determinant of Consumer Preference Reversals. *Journal of Marketing Research, 34*(2), 205–218.

Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. *Marketing Science, 17*(1), 4–28. https://doi.org/10.1287/mksc.17.1.4

Raghubir, P., & Srivastava, J. (2008). Monopoly Money: The Effect of Payment Coupling and Form on Spending Behavior. *Journal of Experimental Psychology: Applied, 14*(3), 213–225. https://doi.org/10.1037/1076-898X.14.3.213

Schwarz, N. (2004). Metacognitive experiences in consumer judgment and decision making. *Journal of Consumer Psychology, 14*(4), 332–348. https://doi.org/10.1207/s15327663jcp1404_2

Sebastian, K.-H. (2013). Warum Preiskämpfer Irren. *Harvard Business Manager*.

Shafir, E., & Thaler, R. H. (2006). Invest now, drink later, spend never: On the mental accounting of delayed consumption. *Journal of Economic Psychology, 27*(5), 694–712. https://doi.org/10.1016/j.joep.2006.05.008

Shefrin, H. M., & Thaler, R. H. (1988). The Behavioral Life-Cycle Hypothesis. *Economic Inquiry, 26*(4), 609–643. https://doi.org/10.1111/j.1465-7295.1988.tb01520.x

Simon, H. (2015). Confessions of the Pricing Man: How Price Affects Everything. Springer: Heidelberg

Simon, H., von der Gathen, A., & Daus, P. W. (2010). Retail Pricing – Higher Profits Through Improved Pricing Processes. In M. Krafft & M. K. Mantrala (Eds.), Retailing in the 21st Century: Current and Future Trends (2nd ed., pp. 319–336). Springer: Heidelberg.

Soetevent, A. R. (2011). Payment Choice, Image Motivation and Contributions to Charity: Evidence from a Field Experiment. American Economic Journal : Economic Policy, 3(1), 180–205.

Soman, D. (2001). Effects of Payment Mechanism on Spending Behavior: The Role of Rehearsal and Immediacy of Payments. Journal of Consumer Research, 27(4), 460–474. https://doi.org/10.1086/319621

Soman, D. (2003). The Effect of Payment Transparency on Consumption: Quasi-Experiments from the Field. Marketing Letters, 14(2001), 173–183. https://link.springer.com/content/pdf/10.1023%2FA%3A1027444717586.pdf

Strelow, E., Heitmann, M., & Kühn, S. (2020). Product Category Priming – A Case Study on Chocolate. *Marketing Review St.Gallen*, 3.

Thaler, R. H. (1985). Mental Accounting and Consumer Choice. Marketing Science, 4(3), 199–214. https://doi.org/10.1287/mksc.4.3.199

Thaler, R. H., Kahneman, D., & Tversky, A. (2000). Mental Accounting Matters. Journal of *Behavioral Decision Making, 206*(September 1998), 241–268.

Thaler, R., & Sunstein, C. (2009). Nudge. Penguin Books: New York.

van Heerde, H. J., Gijsbrechts, E., & Pauwels, K. (2008). Winners and Losers in a Major Price War. *Journal of Marketing Research, 45*(5), 499–518.

White, R. (2008). The Mental Accounting of Gift Card versus Cash Gift Funds. *Advances in Consumer Research, 35*, 722.

B. ESSAY I

Rudolph, T., Scheidegger, G., Barth, E., and Linzmajer M. (published). The Dose Makes the Poison: Dynamic Pricing Strategies and Their Influence on Consumers. *Marketing Review St.Gallen.*

The Dose Makes the Poison:
Dynamic Pricing Strategies and Their Influence on Consumers

Co-Authors

Thomas Rudolph [(1)]
Elias Barth [(2)]
Marc Linzmajer [(3)]

Abstract

To study price dynamics of the Swiss online retail market, prices of 1,200 products from 299 retailers were observed for 50 days. The authors identified four dynamic pricing strategies, compared the price changes of pure online and cross-channel retailers and measured how dynamic pricing influences retailers' value for money ratings.

(1) Thomas Rudolph is Professor of Marketing and International Retail Management, Institute of Retail Management, University of St.Gallen, Switzerland (thomas.rudolph@unisg.ch).

(2) Elias Barth is Doctoral Candidate of Marketing, Institute of Retail Management, University of St.Gallen, Switzerland (elias.barth@unisg.ch).

(3) Marc Linzmajer is Director of the Competence Center Shopper Marketing, Inspiration and Pricing & Retail Promoter Program, Institute of Retail Management, University of St.Gallen, Switzerland (marc.linzmajer@unisg.ch).

Management Summary

Latest technology allows retailers to dynamically adapt their prices. As a result, many retailers rethink their current pricing strategy. This article analyzes this development by identifying four dynamic pricing strategies of cross-channel and pure online retailers in the swiss retail market. The article then investigates the consequences of these four strategies on customers' value for money evaluations.

Main Propositions

1. Based on field data from the Swiss retail market this study identifies four dynamic pricing strategies: Same Price Strategy, Hybrid Strategy, Magnitude Strategy and Frequency Strategy.
2. Two-third of retailers still avoid dynamic pricing and follow a same price strategy.
3. Pure online retailers engage significantly more often in dynamic pricing practices than cross-channel retailers.
4. Some extreme pricing strategies can lead to less favorable "value for money" ratings.

Lessons Learned

1. *Open new doors*: Consumers do not perceive dynamic pricing as negative per se. Therefore, retailers should consider the possibility of engaging in dynamic pricing.
2. *Handle with care:* Retailers should be careful in using extreme pricing strategies to avoid less favorable value for money ratings. In doing so, they may use the price magnitude and price fluency thresholds listed in this article as benchmarks.
3. *Trust is good, control is better:* It is crucial for retailers to regularly control their price positioning in comparison to their competitors and evaluate customers' value for money ratings as a potential indicator of consumer trust.

1. Introduction

In the past, menu costs – the costs associated with changing prices (e.g. by reprinting the restaurant menu or a price tag) – have prevented retailers from frequently adapting their prices. Economists refer to this issue as "price stickiness" (e.g. Laidler 1996). In addition, the lack of price comparison websites implied high search costs for consumers looking for the best prices. Under these circumstances, it was more costly and time-consuming for retailers to adapt prices frequently.

However, technology has lowered search costs and increased price transparency. Consumers can easily compare prices and buy the product with the lowest price. As a result, prices are less sticky today. Instead, dynamic pricing strategies have become normal in many industries (e.g. McAfee & te Velde 2006; Abrate et al. 2012). For example, airlines and hotels use algorithms to adjust their prices based on sales and capacity. Gas prices fluctuate heavily with the demand and supply of crude oil, and theme parks adjust prices during holiday seasons. Nowadays, the rise of e-commerce and the low costs of changing a digital price have led to increasing price changes in the retail sector as well. While it is known that big international online retailers, such as Amazon, change their prices several million times a day (Mehta et al. 2018), little is known about the price dynamics of a whole country's online and cross-channel market. It is also unclear to date how consumers perceive different dynamic pricing strategies.

Therefore, this article seeks to analyze to what extent Swiss pure online retailers (PORs) and cross-channel retailers (CCRs) engage in dynamic pricing. To this purpose, the authors observe the most popular online shopping items over a period of fifty days to provide a descriptive analysis of Swiss online price dynamics. Based on this data, the authors identify and categorize the most common dynamic pricing strategies and highlight the differences between PORs and CCRs. Eventually, consumer ratings are used to analyze how the identified dynamic pricing strategies influence consumers' value for money ratings.

2. Conceptual Framework

In line with Klein and Steinhardt (2008), this publication defines dynamic pricing as a pricing strategy in which a retailer adapts prices at any time in reaction to changes in demand or competition to maximize total revenue. Hence, in the context of this research, dynamic pricing only relates to time-based price discrimination. This means every customer sees the same price at the same time.

2.1. Channel Differences in Price Dynamics

From a retailer perspective, PORs have almost no marginal costs when changing prices. Thus, they can quickly react to changing consumer demand or price changes of their competitors without incurring any costs. Therefore, PORs are more likely to change prices more frequently to maximize their profits.

Even though the necessary technology, such as electronic shelf labels (ESLs), has been available for more than two decades, high investment costs for ESLs as well as low consumer acceptance (e.g. due to poor readability and price fairness concerns) have prevented many retailers from switching to this technology (Comtesse 2010). Today, the majority of brick and mortar stores in the DACH area (Germany, Austria, Switzerland) are still equipped with non-electronic shelf labels. As recent literature on multichannel pricing suggests, CCRs should try to synchronize their pricing activities across all channels (Grewal et al. 2010), with only few exceptions (Homburg et al. 2019). Discriminating prices across channels could be perceived as unfair by customers (Xia et al. 2004; Haws & Bearden 2006). In fact, today the majority of CCRs synchronizes its prices and price changes online and offline (Cavallo 2017). Therefore, the authors expect that CCRs are less likely to engage in dynamic pricing:

(H1) Cross-channel retailers will have lower price fluctuations than pure online retailers.

2.2. Effects of Dynamic Pricing

To better understand consumer reactions to dynamic pricing, this study analyses if and how dynamic pricing strategies influence consumers' price perception for Swiss PORs and CCRs. Previous research has shown that dynamic pricing strategies may lead to negative outcomes for retailers (e.g. Garbarino & Lee 2003; Haws & Bearden 2006; Garbarino & Maxwell 2010). This is because demand-based and economically motivated price changes can be considered unfair by customers (Kahneman et al. 1986; Dickson & Kalapurakal 1994; Campbell

1999; Bolton et al. 2003; Xia et al. 2004; Grewal et al. 2004). In an online experiment, Garbarino and Lee (2003) showed that dynamic pricing reduces consumers' trust in the benevolence of retailers. Garbarino and Maxwell (2010) argue that consumers may perceive dynamic pricing as a norm-breaking pricing event leading to unfairness perceptions, reduced trust in the retailer and higher complaint intentions. Haws and Bearden (2006) showed that time-based price differences negatively influence consumers' price fairness perception and purchase satisfaction. Homburg et al. (2019) demonstrate that consumers only accept offline price premiums of approximately 2%. However, field evidence of these negative effects has up to now mainly been limited to media coverage. In fact, public interest in dynamic pricing has increased in recent years. The media has published much anecdotal evidence of consumers' aversion to dynamic pricing practices in different contexts, such as skiing tickets (Auras 2019; Krückl & Bolzli 2019), retailing (Heininger 2018; Mehta et al. 2018) or mobility services (Pfander 2016; Hecking 2019; Sugar 2019). Based on these arguments, the authors assume a negative connection between dynamic pricing and perceived price fairness. Yet, as price fairness perception is hard to measure in secondary field data, the authors will operationalize the theoretical construct of "price fairness perception" by looking at retailers' value for money ratings in the data analysis section. The value for money ratings can be seen as an indicator of price fairness perception ratings as used in previous experimental studies (e.g. Dickson & Kalapurakal 1994; Xia et al. 2004; Garaus et al. 2016).

(H2) Dynamic pricing leads to less favorable value for money ratings of the specific retailer.

Based on H2, the authors expect that consumers shopping at retailers who engage heavily in dynamic pricing show lower levels of perceived value for money. This implies that consumers are able to perceive price differences over time. However, the Weber-Fechner Law (e.g. Monroe 1973; Thaler 1980; Monroe & Lee 1999; Sirvanci 2016) states that there is a difference between the actual change in a stimulus (e.g. a price) and the perceived change of this stimulus (Monroe 1973). Changes below a certain threshold (also known as "just noticeable difference") which vary in proportion to the stimulus will not be noticed by recipients (Britt & Nelson 1976). This means that small and frequent price changes may remain unnoticed by consumers and might not affect consumers' value for money perceptions. In contrast, infrequent and large price changes are expected to lower consumers' value for money perception:

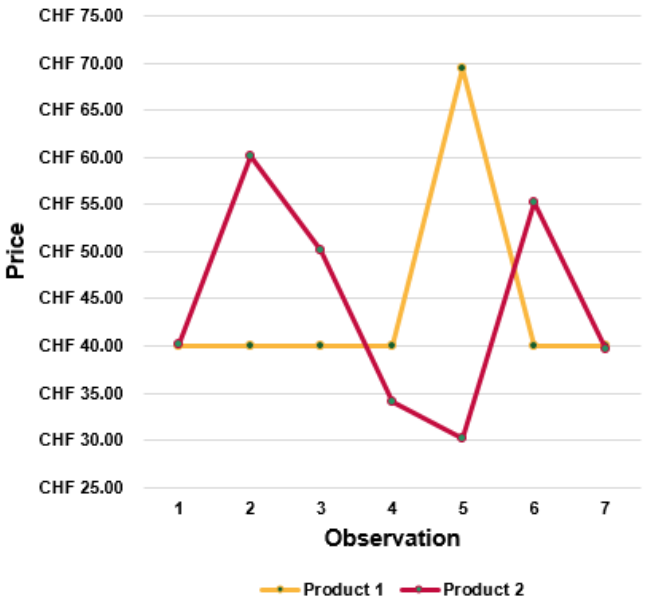
(H3) The magnitude of price changes will have a stronger negative effect on value for money ratings than the frequency of price changes.

3. Data Analysis

3.1. Data Collection

Starting from January 4th and up to February 23rd, 2019 (50 days), the authors collected publicly available price information of 1,200 products from 12 different categories on the Swiss price comparison website "toppreise.ch"[1]. For all of the 1,200 products, prices (excl. shipping costs) were collected three times per day (every 8 hours – at 1 am, 9 am and 5 pm Central European Time)[2] for 50 days using a web-scraping tool. The selected products in the data sample stem from toppreise.ch's list of the 100 most popular products per category. Toppreise.ch uses the number of price searches for a product as an indicator of its popularity. The final, adjusted[3] dataset consists of 3,044,625 data points from 24,817 individual retailer-product combinations. Throughout this article, the authors refer to "retailer-product-combination" as a specific product offered by a specific retailer (e.g. iPhone X sold by digitec.ch ≠ iPhone X sold by microspot.ch).

3.2. Price Fluctuation Metrics



	Product 1	Product 2
t1	CHF 40.00	CHF 40.10
t2	CHF 40.00	CHF 60.15
t3	CHF 40.00	CHF 50.15
t4	CHF 40.00	CHF 34.15
t5	CHF 69.50	CHF 30.15
t6	CHF 40.00	CHF 55.15
t7	CHF 40.00	CHF 39.65

Std.	CHF 10.32	CHF 10.32
Mean	CHF 44.21	CHF 44.21
Rel. Std.	23.35%	23.35%

Figure B-1. Limitations of relative standard deviation as a measure for price fluctuation.

[1] For more information regarding the platform toppreise.ch, visit www.toppreise.ch.
[2] Due to the large amount of data and the complexity of scraping all URLs at the same time, sometimes the data was collected a few minutes behind schedule.
[3] Some of the 1,200 product links were structured differently (about 10%). Therefore, our scraping algorithm did not reliably gather the price information of all products at all times. Consequently, we removed all products with less than 50 price entries (one a day).

In order to determine to which extent Swiss PORs and CCRs engage in dynamic pricing the authors first had to quantify the observed price fluctuations. Economists usually express the fluctuation of prices (e.g. crude oil price; Ferderer 1996) by the standard deviation. The standard deviation expresses the degree of variation in a series of data. Dividing the standard deviation by the mean value of the respective series of data leads to the relative standard deviation. The relative standard deviation makes variation comparable across products of significantly different price categories. While relative standard deviation is an accurate metric to express the price fluctuation of product prices, it has some limitations, as illustrated by the following examples.

Figure B-1 shows the price chart of two exemplary products. Product 2 exhibits various price changes, suggesting a higher variability than in product 1. However, the standard deviation, the mean and thus the relative standard deviation are identical. Product 1 has one relatively large price change, whereas product 2 shows seven rather small variations. Both types of changes influence the mean and standard deviation values in the same way.
To allow differentiated statements on the dynamics of product prices over time, price fluctuation was calculated in two different ways:

1. price fluctuation as an expression of the magnitude of price changes and
2. price fluctuation as an expression of the frequency of price changes.

The relative standard deviation formula was used to calculate price fluctuation magnitude (PFM): The standard deviation of product A's price sold by retailer B over 50 days was divided by the mean price of product A sold by retailer B and multiplied by 100. In doing so, the result is a percentage value that can compare the PFM of various products, even if their average prices are significantly different (e.g. iPhone X vs LEGO set). Price fluctuation frequency (PFF), on the other hand, is calculated by counting the number of distinct prices product A is offered for by retailer B over the period of 50 days, divided by the total number of price observations for product A at retailer B. If a product shows no price fluctuations at all, the distinct price count will be at least 1. Therefore, 1 is subtracted from the count of distinct prices before it is divided by the total number of price observations. The calculations are summarized in the formulas below:

$$\textbf{(1)}\ \boldsymbol{PFM\ in}\ \% = \frac{\boldsymbol{Standard\ deviation\ (product\ price)}}{\boldsymbol{Mean\ (product\ price)}} * \mathbf{100}$$

$$\textbf{(2)}\ \boldsymbol{PFF\ in}\ \% = \frac{\boldsymbol{Number\ of\ distinct\ prices\ per\ item\ and\ retailer - 1}}{\boldsymbol{Number\ of\ price\ entries\ per\ item\ and\ retailer}} * \mathbf{100}$$

3.3. Cluster Analysis

In the next step, the authors used the fluctuation metrics to measure how actively retailers engage in dynamic pricing. In addition, to identify dominant pricing strategies, x-means cluster analysis was performed to categorize all 299 retailers according to their average price fluctuation magnitude and frequency values. X-means is a clustering algorithm based on k-means clustering which helps to identify the accurate group numbers more efficiently based on the Bayesian and Akaike information criteria (Pelleg & Moore 2000). The calculations led to an optimal group size of 4 with an average cluster distance of 0.598 and a Davies–Bouldin index of 0.802 (Davies & Bouldin 1979). Figure B-2 illustrates the following four dynamic pricing strategy clusters:

- About two thirds of the observed retailers still avoid dynamic pricing. Instead, they fall into the Same Price Strategy cluster. In this cluster, retailers stick to their prices and avoid price changes.
- The Hybrid Strategy is the second largest cluster observed, with 24% of retailers. It is characterized by moderate price changes in both price dimensions.
- Two extreme strategies were identified: 11% of retailers fall into the Magnitude Strategy cluster, which shows high PFM and low to moderate PFF values.
- In contrast to this, the Frequency Strategy exhibits high PFF and low to moderate PFM values.

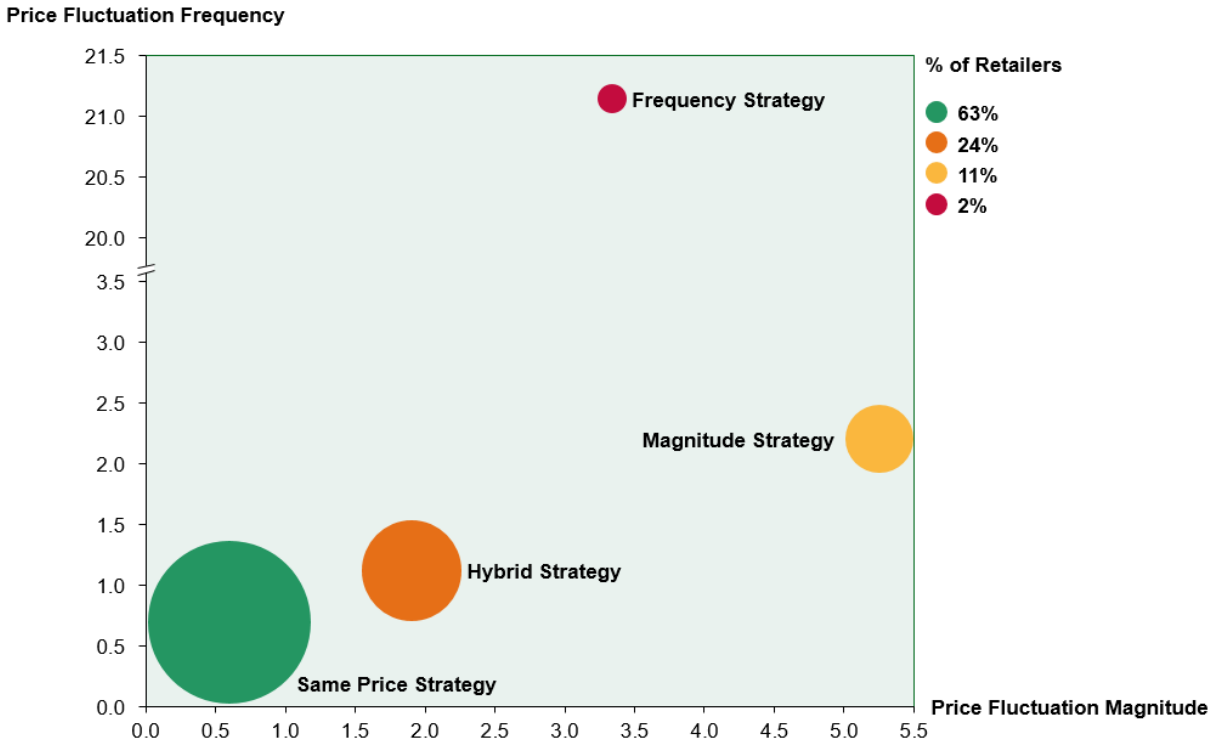
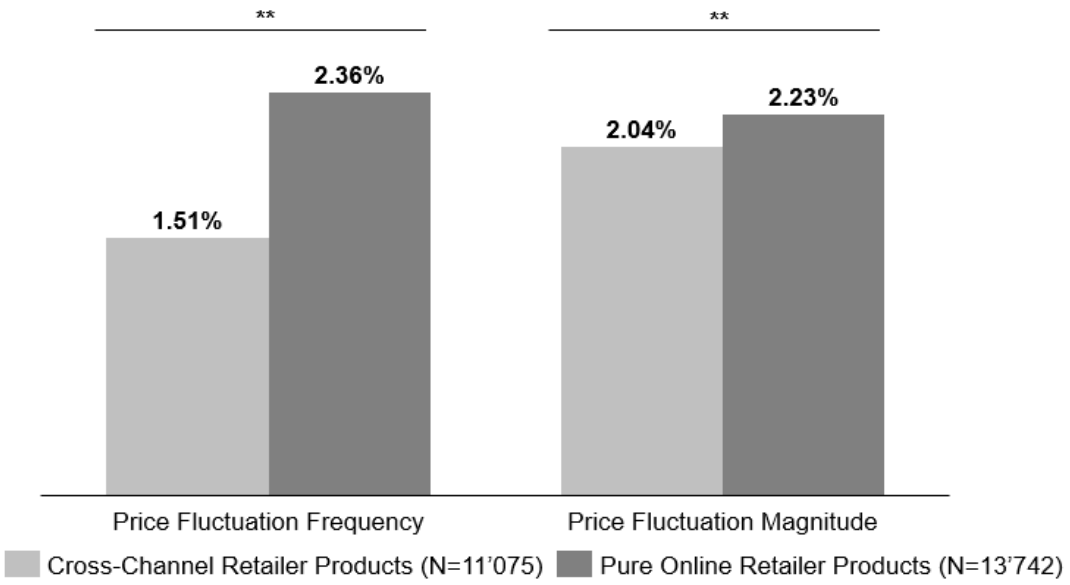


Figure B-2. Dynamic pricing strategy clusters.

3.4. Channel Differences

The authors conducted an independent-samples t-test to assess the influence of retail formats (PORs and CCRs) on the formulation of pricing strategies. First, all retailers were coded according to their retail format using the information available on the retailers' web-sites. Retailers without any brick and mortar stores were considered as PORs. Online retailers with a pick-up station also fell into this category, as the products can still not be bought off-fline. Then, price fluctuation differences of all retailer-product combinations (N = 24,817) were compared between the two retail formats. CCRs (M = 1.51%, SD = 3.44%) showed significantly lower ($t(24{,}648.92) = -18.19$, $p < 0.001$) PFF scores than PORs (M = 2.36%, SD = 3.93%). The same holds true for PFM scores. Again, CCRs' scores (M = 2.04%, SD = 4.41%) were significantly lower ($t(21{,}168.38) = -3.60$, $p < 0.001$) than those of PORs (M = 2.23%, SD = 3.59%). In sum, product prices offered at PORs are more dynamic than prices offered at CCRs. The results illustrated in Figure B-3 confirm H1: CCRs show lower levels of price fluctuations.



**p < 0.001

Figure B-3. Mean fluctuation differences between cross-channel and pure online retailers.

3.5. Effects of Dynamic Pricing

After identifying the most common pricing strategies, consumer ratings from toppreise.ch were used to evaluate price fluctuation effects on consumers' value for money ratings. Based on previous research, the authors hypothesized that dynamic pricing leads to negative price fairness perceptions. To allow differentiated statements on how each pricing strategy influences price fairness perception, both price fluctuation dimensions (magnitude and frequency) were considered in the following calculations.

For this analysis, 105,469 retailer ratings in the category "value for money" were added to the dataset.[4] On toppreise.ch, consumers can rate all retailers across different categories on a scale from 1 to 6. In an ordinary least squares regression with mean-centered PFF values, as well as mean-centered PFM values, their interaction as predictors, and value for money ratings as a dependent variable, the influence of price dynamics on consumer perceptions was tested. While the overall regression model was significant ($F(3, 171) = 5.813$, $R^2 = 9.250\%$, $p < 0.001$), only PFM ($b = –0.106$, $p < 0.001$) had a significant negative influence on consumers' value for money ratings. PFF ($b = –0.013$, $p = 0.35$) and the interaction term ($b = 0.012$, $p = 0.51$) had no significant effect on the ratings. As the sample sizes in extreme clusters were low ($N < 30$), a statistical analysis for average group differences between the four pricing strategies could not be performed. However, as illustrated in Figure B-4, it can be seen that retailers using a same price or hybrid strategy show nearly identical ratings, while frequency and magnitude strategies lead to less favorable perceptions of retailers' value for money.

Even though the differences are statistically significant, the nominal differences are rather small. However, given the competitive environment of PORs and CCRs, even such a small difference could potentially lead to a shift in consumers' shop preferences.

[4] Out of 299 retailers, 175 were rated by customers.

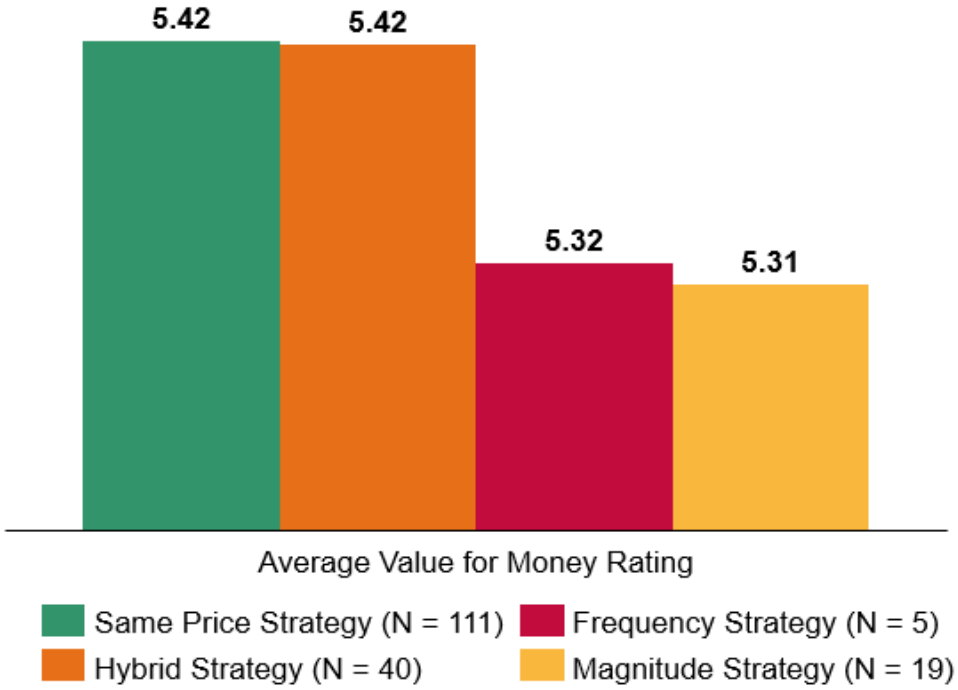


Figure B-4. Average value for money ratings by pricing strategy.

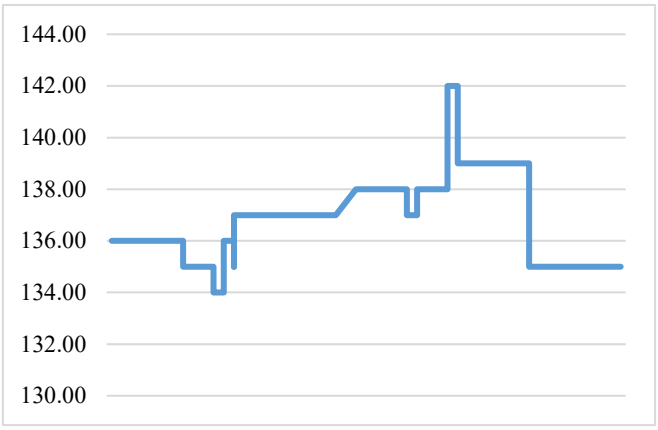
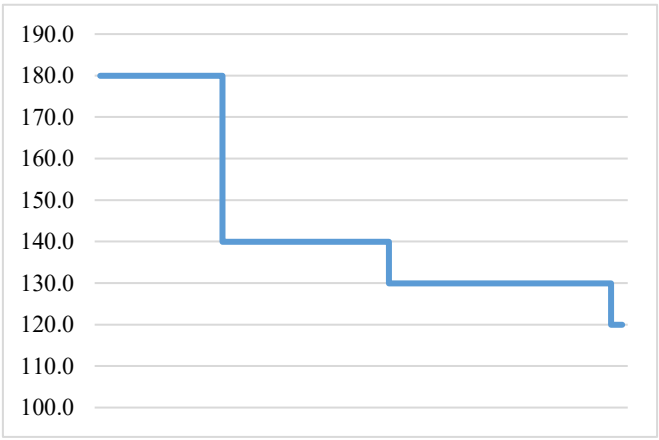
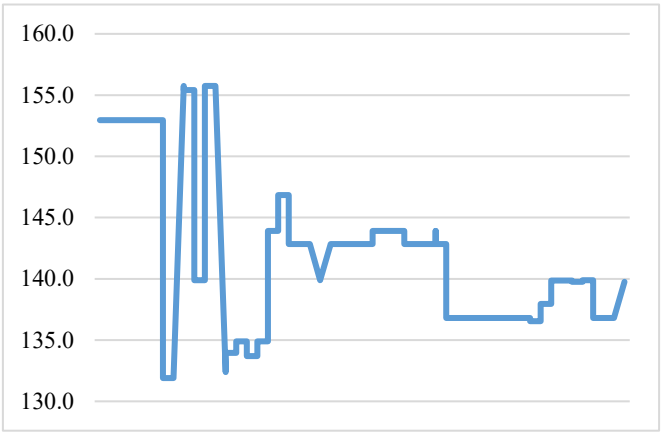
4. Implications for Retailers and Marketing Research

Table B-1 illustrates the real-life mapping of the introduced pricing strategies for the same product "LEGO Technic – Mack Anthem" over the exact same time period of 50 days. Lego products are known to exhibit a stable price development and are easy to compare (Sielen 2013). Nevertheless, the table shows how heterogeneous retailers are in their pricing approach for the same product. Also, in accordance with the proposed hypothesis, the table shows that PORs (Galaxus and Techmania) engage more actively in dynamic pricing than retailers with a brick and mortar presence (Lego and Toys "R" Us).

Overall, the results of the cluster analysis indicate that retailers are still cautious in their adoption of dynamic pricing. However, the dominance of the same price strategy is surprising. After all, researchers have shown that dynamic pricing can significantly increase profitability (Zhao & Zheng 2000; Sahay 2007). Retailers used to avoid price changes because of the high costs associated with them (e.g. menu costs). However, information technology has significantly lowered those marginal costs for online retailers as well as for CCRs. Still, as shown in this study, some CCRs do not yet take advantage of the new technologies and therefore show lower levels of price fluctuation than PORs.

An alternative reason behind the reluctance to use dynamic pricing might be the fear of negative value for money ratings. However, the findings on the effects of dynamic pricing suggest that only the extreme strategies—and especially the magnitude of price changes—lead to negative value for money ratings. There is almost no difference in value for money ratings between the same price strategy and the Hybrid Strategy. Therefore, consumers do not consider dynamic pricing as negative per se. Only if consumers feel disadvantaged, they perceive prices as unfair, which in turn can lead to lower value for money ratings (Bolton et al. 2003). Therefore, instead of avoiding dynamic pricing altogether, retailers should consider adopting dynamic pricing to increase profitability while maintaining perceived price fairness. As previous research has pointed out, price fairness perception is highly dependent on factors like motives for price changes and competitive prices (Campbell 1999; Bolton et al. 2003).

Table B-1. Four strategies for the same product "LEGO Technic – Mack Anthem"

Strategy	Price development over 50 days	Shop	Type	Metrics	
Same Price		SHOP	Cross Channel	Distinct Prices	1
				Max Price	CHF 199
				Min Price	CHF 199
Hybrid		GALAXUS	Pure Online	Distinct Prices	7
				Max Price	CHF 142
				Min Price	CHF 134
Magnitude		toysrus	Cross Channel	Distinct Prices	4
				Max Price	CHF 179.90
				Min Price	CHF 119.90
Frequency		tech mania	Pure Online	Distinct Prices	17
				Max Price	CHF 155.80
				Min Price	CHF 131.90

Thus, retailers who switch from a same price strategy to a dynamic pricing strategy (e.g. Hybrid Strategy) should consider those factors in their pricing strategy. This implies to not only monitor the value for money ratings carefully and to track price fairness with established measurements like the scale items used by Campbell (1999). It also means to clearly communicate the motives behind price changes. For example, retailers may refer to rising costs of raw materials for battery production when increasing the price of a digital camera – assuming, of course, that this is true. In addition, retailers should evaluate their current strategy positioning (same price, hybrid, frequency, magnitude) in comparison to their competitors. Numerous web scraping algorithms, like the one used for this research, simplify the process of gathering price information from competitors. With this publicly available information, retailers can identify their current dynamic pricing positioning compared to their competitors. Retailers who are using one of the two extreme strategies should be aware that their current pricing strategy might lower their value for money ratings. Figure B-5 provides an overview of the positioning of the pricing strategies that are currently used by Swiss retailers.

The following quote by the Swiss toxicologist Paracelsus (1538/1965, p. 510) nicely sums up the most important implication for retailers: "All things are poison, and nothing is without poison, the dosage alone makes it so a thing is not a poison." In this vein, dynamic pricing is only poisonous to retailers if the dose is too high. But how high is “too high”? While the answer to this question certainly depends on the individual retailer’s product category, competitive environment and consumers’ price sensitivity, we seek to provide some guidance by listing the PFM and PFF ranges for the different strategy clusters in Table B-2. Especially retailers with a weak market position, whose pricing decisions are often influenced by their competitors, can use the value ranges as benchmarks.

According to our findings, retailers should try to avoid extreme PFM values over 3.71% and PFF values over 3.66% (maximum values of the hybrid strategy). PFM values should be handled with more care as their negative impact on consumers’ value for money evaluations is higher. This means that over an observation period of 50 days with three daily price observations (150 price observations in total), the price should not be adjusted more than 6 times. At the same time, the standard deviation caused by those price changes should not be higher than CHF 3.71, if we assume a mean price of CHF 100 over the observation period.[5]

[5] Please note: As shown in Figure B-1, many different price combinations can lead to a standard deviation of over CHF 3.71. For example, if six out of 150 price observations are CHF 80 and all other 144 observations are CHF 101, the standard deviation is CHF 4.12 and thus already exceeds the threshold.

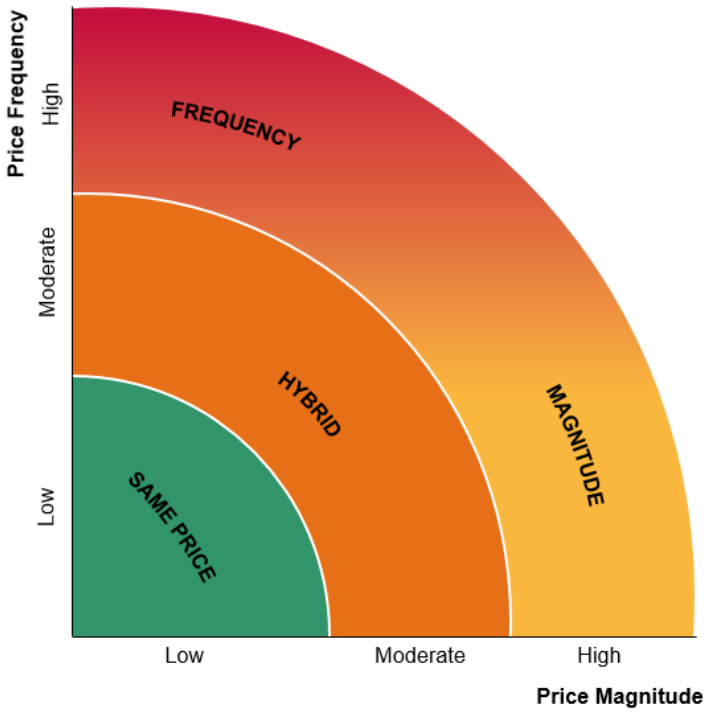


Figure B-5. Dynamic pricing strategy classification.

From a theoretical perspective, this paper contributes to existing research on dynamic pricing as the self-developed metrics allow retailers and future researchers to quantify the use of dynamic pricing and differentiate between two fluctuation dimensions: frequency and magnitude of price changes. In addition, it fills a gap in the price fairness literature as it provides field evidence on how changes in price fluctuation frequency and price fluctuation magnitude affect consumers' value for money ratings. Lastly, the findings on channel differences underline the importance of menu cost considerations in the context of dynamic pricing and thereby contribute to the economic literature on market inefficiencies and the establishment of equilibrium prices. As a next step toward a better understanding of dynamic pricing in retail, an in-depth analysis of the interplay between business model type and dynamic pricing strategies may lead to new insights for practitioners and researchers alike.

Table B-2. PFM and PFF ranges.

	PFM Range	**PFF Range**
Same Price Strategy	0.00% – 1.07%	0.00% -1.36%
Hybrid Strategy	0.79% - 3.71%	0.12% - 3.66%
Magnitude Strategy	2.01% - 25.99%	0.37% - 8.44%
Frequency Strategy	1.20% - 7.25%	14.53% - 33.58%

References

Abrate, G., Fraquelli, G., & Viglia, G. (2012). Dynamic pricing strategies: Evidence from European hotels. *International Journal of Hospitality Management*, *31*(1), 160–168. https://doi.org/10.1016/J.IJHM.2011.06.003

Auras, M. (2019). Dynamische Skipasspreise: Fluch oder Segen? Basler Zeitung. https://blog.bazonline.ch/outdoor/index.php/73633/dynamische-skipasspreise-fluch-oder-segen/

Bolton, L. E., Warlop, L., & Alba, J. W. (2003). Consumer Perceptions of Price (Un)Fairness. *Journal of Consumer Research*, *29*(4), 474–491. https://doi.org/10.1086/346244

Britt, S. H., & Nelson, V. M. (1976). The marketing importance of the "Just Noticeable Difference." *Business Horizons*, *19*(4), 38–40. https://doi.org/https://doi.org/10.1016/0007-6813(76)90063-X

Campbell, M. C. (1999). Perceptions of Price Unfairness : Antecedents and Consequences. *Journal of Marketing Research*, *36*(2), 187–199.

Cavallo, A. (2017). Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers. *American Economic Review*, *107*(1), 283–303.

Comtesse, M. (2010). Digitale Preisschilder fallen bei Kunden durch. Berner Zeitung. https://www.bernerzeitung.ch/schweiz/standard/digitale-preisschilder-fallen-bei-kunden-durch/story/31278829

Davies, D. L., & Bouldin, D. W. (1979). A Cluster Separation Measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *1*(2), 224–227. https://doi.org/10.1109/TPAMI.1979.4766909

Dickson, P. R., & Kalapurakal, R. (1994). The use and perceived fairness of price-setting rules in the bulk electricity market. *Journal of Economic Psychology*, *15*(3), 427–448. https://doi.org/10.1016/0167-4870(94)90023-X

Ferderer, P. J. (1996). Oil price volatility and the macroeconomy. *Journal of Macroeconomics*, *18*(1), 1–26. https://doi.org/10.1016/S0164-0704(96)80001-2

Garaus, M., Wolfsteiner, E., & Wagner, U. (2016). Shoppers' acceptance and perceptions of electronic shelf labels. *Journal of Business Research*, *69*(9), 3687–3692. https://doi.org/10.1016/J.JBUSRES.2016.03.030

Garbarino, E., & Lee, O. F. (2003). Dynamic Pricing in Internet Retail: Effects on Consumer Trust. *Psychology & Marketing*, *20*(June 2003), 495–513. https://doi.org/10.1002/mar.10084

Garbarino, E., & Maxwell, S. (2010). Consumer response to norm-breaking pricing events in e-commerce. *Journal of Business Research*, *63*(9–10), 1066–1072. https://doi.org/10.1016/j.jbusres.2008.12.010

Grewal, D., Hardesty, D. M., & Iyer, G. R. (2004). The effects of buyer identification and purchase timing on consumers' perceptions of trust, price fairness, and repurchase intentions. *Journal of Interactive Marketing*, *18*(4), 87–100. https://doi.org/10.1002/dir.20024

Grewal, D., Janakiraman, R., Kalyanam, K., Kannan, P. K., Ratchford, B., Song, R., & Tolerico, S. (2010). Strategic Online and Offline Retail Pricing: A Review and Research Agenda. *Journal of Interactive Marketing*, *24*(2), 138–154. https://doi.org/10.1016/J.INTMAR.2010.02.007

Haws, K. L., & Bearden, W. O. (2006). Dynamic Pricing and Consumer Fairness Perceptions. *Journal of Consumer Research*, *33*(3), 304–311.

Hecking, M. (2019). Wie die KI uns abkassiert - meist unbemerkt. Manager Magazin. https://www.manager-magazin.de/lifestyle/artikel/dynamische-preise-wie-uns-kuenstliche-intelligenz-unbemerkt-abkassiert-a-1259049.html

Heininger, B. (2018). Dynamic Pricing: Tausend Kunden, tausend Preise. Handelszeitung. https://www.handelszeitung.ch/unternehmen/dynamic-pricing-tausend-kunden-tausend-preise

Homburg, C., Lauer, K. & Vomberg, A. (2019). The multichannel pricing dilemma: do consumers accept higher offline than online prices? *International Journal of Research in Marketing*. https://doi.org/10.1016/j.ijresmar.2019.01.006.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness as a Constraint on Profit Seeking: Entitlements in the Market. *The American Economic Review*, *76*(4), 728–741. https://doi.org/10.2307/1806070

Klein, R., & Steinhardt, C. (2008). Revenue Management: Grundlagen und Mathematische Methoden. Springer-Verlag.

Koschate-Fischer, N., & Wüllner, K. (2017). New developments in behavioral pricing research. *Journal of Business Economics*, *87*(6), 809–875. https://doi.org/10.1007/s11573-016-0839-z

Krückl, G., & Bolzli, M. (2019). Droht bei dynamischen Preise in Skigebieten Zweiklassengesellschaft? Nau.Ch. https://www.nau.ch/news/wirtschaft/droht-bei-dynamischen-preise-in-skigebieten-zweiklassengesellschaft-65484364

Laidler, D. (1996). Wage and Price Stickiness in Macroeconomics: Historical Perspective. In F. Capie & G. E. Wood (Eds.), *Monetary Economics in the 1990s: The Henry Thornton Lectures, Numbers 9-17* (pp. 92–121). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-25204-6_6

McAfee, P., & te Velde, V. L. (2006). Dynamic Pricing in the Airline Industry. In T. J. Hendershott (Ed.), *Handbook on Economics and Information Systems* (pp. 527–570). Elsevier.

Mehta, N., Detroja, P., & Agashe, A. (2018). Amazon changes prices on its products about every 10 minutes — here's how and why they do it. Business Insider. https://www.businessinsider.com/amazon-price-changes-2018-8?r=US&IR=T

Monroe, K. B. (1973). Buyers' Subjective Perceptions of Price. *Journal of Marketing Research*, *10*(1), 70. https://doi.org/10.2307/3149411

Monroe, K. B., & Lee, A. Y. (1999). Remembering versus Knowing: Issues in Buyers' Processing of Price Information. *Journal of the Academy of Marketing Science*, *27*(2), 207–225. https://doi.org/10.1177/0092070399272006

Paracelsus, T. (1538/1965). Die dritte Defension wegen des Schreibens der neuen Rezepte. W.-E. Peuckert (Ed.), Septem Defensiones 1538, Werke Bd 2. (pp. 508–513). Darmstadt: Wissenschaftliche Buchgesellschaft.

Pelleg, D., & Moore, A. (2000). X-means: Extending K-means with Efficient Estimation of the Number of Clusters. *Proceedings of the 17th International Conf. on Machine Learning*.

Pfander, M. (2016). So tricksen die Airlines bei Flugticket-Preisen. Tages Anzeiger. https://www.tagesanzeiger.ch/wirtschaft/unternehmen-und-konjunktur/flugtickets-das-sind-die-tricks-der-airlines/story/23832633

Sahay, A. (2007). How to Reap Higher Profits With Dynamic Pricing. *MIT Sloan Management Review*, *48*(4), 53–60.

Sielen, A. (2013). What Happened with LEGO. Realityprose.Com. http://www.realityprose.com/what-happened-with-lego/

Sirvanci, M. B. (2016). An Empirical Study Of Price Thresholds And Price Sensitivity. *Journal of Applied Business Research, 9* (2). https://doi.org/10.19030/jabr.v9i2.6075

Sugar, R. (2019). Uber Is Sorry About All the Bad Stuff. Bloomberg Opinion. https://www.bloomberg.com/opinion/articles/2019-04-12/uber-is-sorry-about-all-the-bad-stuff

Thaler, R. H. (1980). Toward a Positive Theory of Consumer Choice. *Journal of Economic Behavior and Organization*, *1*(March), 39–60.

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The Price is Unfair! A Conceptual Framework of Price Fairness Perceptions. *Journal of Marketing*, *68*(October), 1–15.

Zhao, W., & Zheng, Y. S. (2000). Optimal Dynamic Pricing for Perishable Assets with Nonhomogeneous Demand. *Management Science*, *46*(3), 375–388. https://doi.org/https://doi.org/10.1287/mnsc.46.3.375.12063

C. ESSAY II

Scheidegger, G., Linzmajer, M., and Rudolph, T. (published). Price Discount Strategies in Times of Increasing Price Transparency: How Price Consciousness and Price Comparison Moderate the Effect of Discount Strategy on Store Price Image. *Die Unternehmung: Swiss Journal of Business Research and Practice.*

Price Discount Strategies in Times of Increasing Price Transparency: How Price Consciousness and Price Comparison Moderate the Effect of Discount Strategy on Store Price Image

Co-Authors

Marc Linzmajer[(1)]

Thomas Rudolph[(2)]

Abstract

This research uses a large set of price promotion field data to better understand the application of price discount strategies by Swiss grocery retailers. Taking the prevalence of these strategies in the Swiss grocery retail market as a basis, we use an online experiment that builds on recent developments in technology usage by consumers and investigate the impact of price comparison on store price image. The results show that Swiss grocery retailers have increased their number of discounts offered over the observation period of two years. In addition, store price image significantly improved with the number of discounted products offered. On the other hand, discount depth had no influence on store price image. These effects, however, are dependent on consumers' price consciousness and their (non-) usage of a price comparison tool. Lastly, theoretical and practical implications are being provided.

(1) Marc Linzmajer is Director of the Competence Center Shopper Marketing, Inspiration and Pricing & Retail Promoter Program, Institute of Retail Management, University of St.Gallen, Switzerland (marc.linzmajer@unisg.ch).

(2) Thomas Rudolph is Professor of Marketing, Institute of Retail Management, University of St.Gallen, Switzerland (thomas.rudolph@unisg.ch).

Zusammenfassung

Trotz kontroverser Diskussionen um die Wirkung unterschiedlicher Preisreduktionsstrategien, fehlt es an empirischer Evidenz zur Anwendung und Verbreitung dieser Strategien in kompetitiven Handelslandschaften. Der vorliegende Beitrag untersucht anhand eines Felddatensatzes zunächst, welche Preisreduktionsstrategien Schweizer Lebensmitteldetailhändler anwenden. In einem darauffolgenden Online-Experiment analysieren wir die Auswirkungen dieser Preisreduktionsstrategien sowie die Nutzung von Preisvergleichsseiten auf das Preisimage von Händlern. Unsere Ergebnisse zeigen, dass die Schweizer Lebensmitteleinzelhändler über den Beobachtungszeitraum von zwei Jahren die Anzahl der angebotenen Rabatte erhöht haben, die Rabatthöhen sich jedoch deutlich unterscheiden. Im Online-Experiment weisen wir einen positiven Effekt der Erhöhung der Anzahl preisreduzierter Produkte auf das Preisimage eines Händlers nach. Gleichzeitig hat die Veränderung der Rabatthöhen keinen Einfluss auf das Preisimage. Die beschriebenen Effekte sind abhängig von der Preiswahrnehmung eines Verbrauchers und der (Nicht-)Nutzung von Preisvergleichsseiten. Abschliessend diskutieren wir theoretische und praktische Implikationen unserer Studie.

1. Introduction

Intensifying competition and price-sensitive customers have forced grocery retailers into a promotion-trap (Fassnacht & El Husseini, 2013) with plenty of negative economic consequences (Heil & Helsen, 2001). In addition to so called "high-low" retailers (Hi-Lo), even traditional every-day-low-price retailers (EDLPs)[1], such as the German-based discounter 'Lidl' have recently started offering large price cuts on a regular basis (Lidl, 2019). Companies intensify their promotion activity, although extant research has not been able to unequivocally confirm the hoped-for positive long-term effects of price discounts on important company metrics such as store price image, sales or profit (e.g., Blattberg & Neslin, 1989; Cai, Bagchi, & Gauri, 2016; Mulhern & Leone, 1990; van Doorn & Hoekstra, 2013; Walters & MacKenzie, 1988). More specifically, it remains unclear how to balance discount frequency and discount depth while increasing promotion activity in general.

Against this background, two price discount strategies dominate in retail contexts: offering shallow but frequent discounts vs. offering deep and infrequent discounts (e.g., Levy, Weitz, & Grewal, 2014). But so far, there is no evidence on the usage of one or the other strategy to offer the "lowest" price. The trend towards the lowest price is accelerated by increasing price and information transparency (Diehl, Kornish, & Lynch, 2003) and the ubiquity of mobile internet devices (Dekimpe & Geyskens, 2019). From a behavioral angle, frequent and deep discounts shape the customers' reference prices and make them more price- and discount-sensitive in the long-run (Dekimpe, Hanssens, & Silva-Risso, 1998; Kalwani & Yim, 1992; Kaul & Wittink, 1995; Mela, Gupta, & Lehmann, 1997; Pauwels, Hanssens, & Siddarth, 2002). Today, a significant number of consumers visit price comparison websites or online retailers, such as Amazon.com, while standing in front of a shelf at a brick-and-mortar retailer (Brynjolfsson, Hu, & Rahman, 2013; Cao, 2019; Falk, Kunz, Schepers, & Mrozek, 2016). Thereby, the researched prices serve as reference prices when evaluating subsequent prices at local stores (Bodur, Klein, & Arora, 2015; Falk et al., 2016; Jung, Cho, &

[1] ''[…] two strategies often used in retailing [...] are the everyday low prices (EDLP), or always low prices, which may be a philosophy applied by discount stores, and the high and low prices (Hi–Lo), or promotional prices more typical of hypermarkets." (Cataluña, Sánchez Franco, & Villarejo Ramos, 2005, p. 331). Thus, Hi-Lo and EDLP are the two dominant retailing formats. EDLP refers to shops offering low prices at all times and Hi-Lo refers to retailers selling their products at a higher average price with frequent price discounts (Fassnacht & El Husseini*, 2013;* Hoch et al*.*, 1994). However, pure versions of EDLPs and Hi-Lo retailers are rare in practice. Therefore, "[EDLP and Hi-Lo] is best thought of a continuum" (Bell & Lattin*,* 1998, p. 67f.). In this article we look at retailers at both sides of the continuum, which we classify as "EDLPs" and "Hi-Lo retailers".

Lee, 2014), which might change the effect of companies' price discount strategy on consumers' store price image.

This article represents one of the first studies to address both the prevalence of discount strategies in a competitive and more transparent market than ever before and to investigate how the increased price comparison ability of consumers affects store price image perceptions. More precisely, two factors converge to create a unique research opportunity: First, we are able to gather and analyze real market data on price promotion strategies of the largest Swiss grocery retailers regarding their number of discounts and discount depth. Second, in light of increased price transparency, we mirror the prevalence of the dominant price discount strategies in an online experiment to investigate how price comparisons—even for unrelated products—and consumers' price consciousness influence the relationship between a retailer's discount strategy (deep vs. frequent discounts) and a consumers' store price image perceptions.

This article proceeds as follows. After analyzing the price discount strategies among the largest Swiss grocery retail companies over a period of two years, an experimental online study investigates effects of price comparison combined with price consciousness on store price image perceptions. The paper concludes by discussing the theoretical contributions and practical implications.

2. Study 1: Field Evidence on Discount Strategies

2.1. Conceptual Background

Although price discounts are a popular research subject for many decades, empirical evidence on the issue of balancing discount frequency vs. discount depth are inconclusive. Hoch, Drèze and Purk, (1994) found that increasing the frequency of shallow price deals led to an increase in unit volume and profit. Small but frequent discounts are more likely to foster a low price image compared to infrequent promotions with deep discounts (Alba, Broniarczyk, Shimp, & Urbany, 1994; Alba, Mela, Shimp, & Urbany, 1999). Danziger, Hadar and Morwitz (2014) find that under price uncertainty, consumers are more likely to choose a retailer offering shallow but frequent discounts, compared to a retailer offering high and infrequent discounts. In a natural experiment, Mulhern and Leone (1990) reported that a change from offering deep but infrequent discounts to shallow and frequent promotions led to a short-term increase in sales but did not affect store traffic. On the other hand, deep discounts are associated with increased traffic, which leads to increased sales of additional products (Bliss, 1988; Gauri, Ratchford, Pancras, & Talukdar, 2017; Lal & Rao, 1997; Levy, Weitz, & Grewal, 2014).

Because there is support for both strategies in different retail contexts—small and frequent vs. deep and infrequent promotions—there is no consensus on which one is superior. In a similar vein, there is no evidence on the prevalence of each strategy in competitive retail markets. By analyzing a large set of market data, we therefore seek to identify the retailers preferred price discount strategy before testing the influence of this specific strategy on consumers' store price image with an online experiment.

2.2. Method

We compiled price promotion data from four major Swiss brick-and-mortar grocery retailers (two Hi-Lo and two EDLP retailers) with a combined market share of over 80 % in Swiss grocery retailing (Lebensmittel Zeitung, 2018). For 107 calendar weeks (December 29, 2014 until December 30, 2016), we collected the prices and discounts of 23,495 grocery items (EDLP: 5,506, Hi-Lo: 17,989) using the information published in the four retailers' weekly promotional brochures. We exclusively included price discounts on food items, while excluding non-food items and non-price discounts such as "2 for 1" or "200 additional loyalty points" promotions. We then analyzed the development of the number of weekly discounted items as well as the average discount depth over time.

2.3. Results

2.3.1. Absolute number of discounts

A simple linear regression analysis was used to test whether calendar weeks (coded from 1 to 107, starting with the week of December 29, 2014) significantly predicted the weekly promotions of the four retailers. The results of the regression ($F(1, 106) = 95.49$, $R^2 = 47.62$ %) indicate that the calendar week ($\beta = 1.13$, $p < 0.001$) significantly influences the number of discounts. We can therefore conclude that the absolute number of discounts significantly increased across the observed time span. In addition, when analyzed separately, we can observe the same trend across both retail formats (see regression plot in Figure C-1): For the two EDLP grocery retailers ($F(1, 106) = 78.91$, $R^2 = 42.91$ %) the calendar weeks significantly predicted the number of discounts per calendar week ($\beta = 0.34$, $p < 0.001$). The same holds for the two Hi-Lo retailers ($F(1, 106) = 64.44$, $R^2 = 38.03$ %, $\beta = 0.79$, $p < 0.001$).

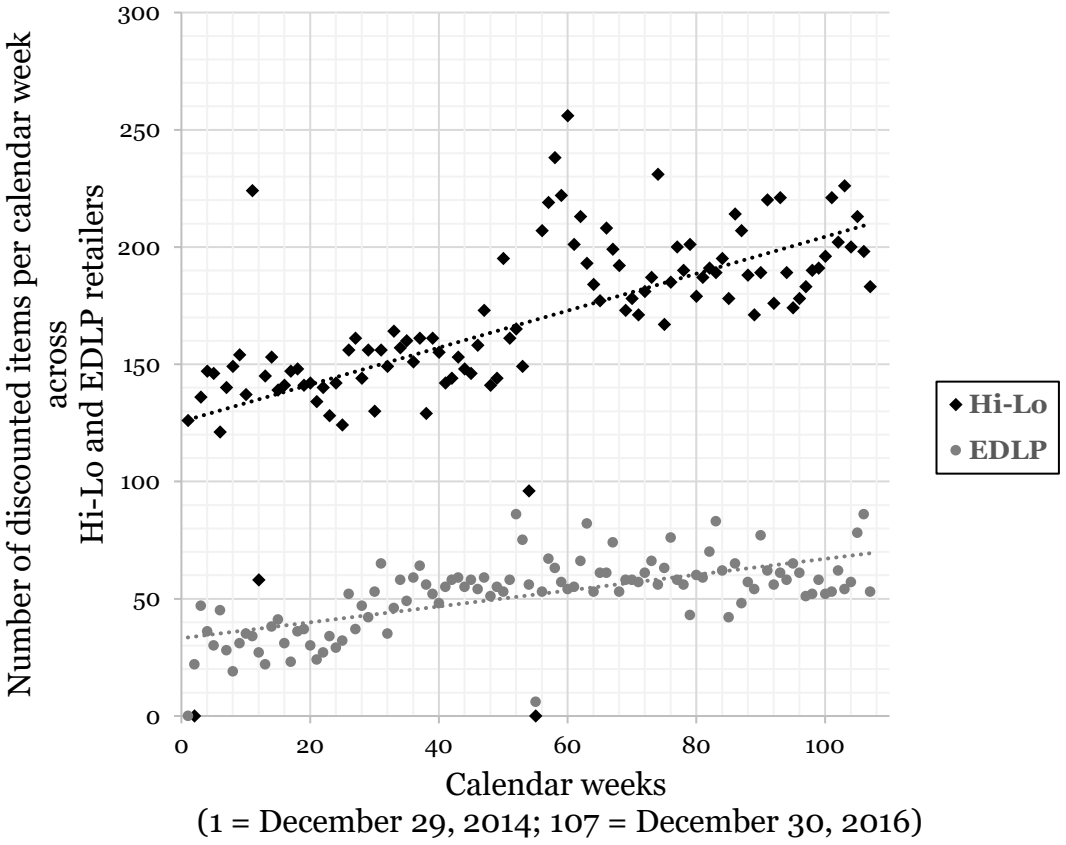


Figure C-1. Number of promotions per week as a function of time across two retail formats Hi-Lo and EDLP (each represented by two retailers).

2.3.2. Discount depth

In a second step, we compared the discount depths across the retail formats and years to analyze the retailers' strategic promotion decisions in times of increasing price transparency. Therefore, we looked at the average promotion depth in 2015 and compared it to the average percentage discounts given in 2016. We conducted a Welch's t-test in order to control for unequal sample sizes and violated assumptions of equal variances. The comparison of average discounts among the Hi-Lo retailers revealed a significant increase ($F(1, 17{,}988 = 37.74$, $p < 0.001$) of the average discounts offered in 2016 ($M = 27.36$ %, $SE = 0.10$ %) compared to the previous year's average ($M = 26.42$ %, $SE = 0.11$ %). On the other hand, EDLP retailers offered significantly lower ($F(1, 5{,}506) = 34.45$, $p < 0.001$) percentage discounts in 2016 ($M = 32.86$ %, $SE = 0.16$ %) than in the previous year ($M = 34.30$ %, $SE = 0.19$ %).

Over the observed time span of approximately two years, we were able to observe two major developments. First, all four retailers, independent of their overall pricing strategy (EDLP or Hi-Lo), are increasing their number of discounted products. We see this as a result of increasing price competition. Second, and maybe more interestingly, the retailers follow

different discount strategies regarding discount depth. Whereas EDLP retailers tend to lower the percentage discounts they offer, Hi-Lo retailers offer their customers even higher discounts (see Figure C-2).

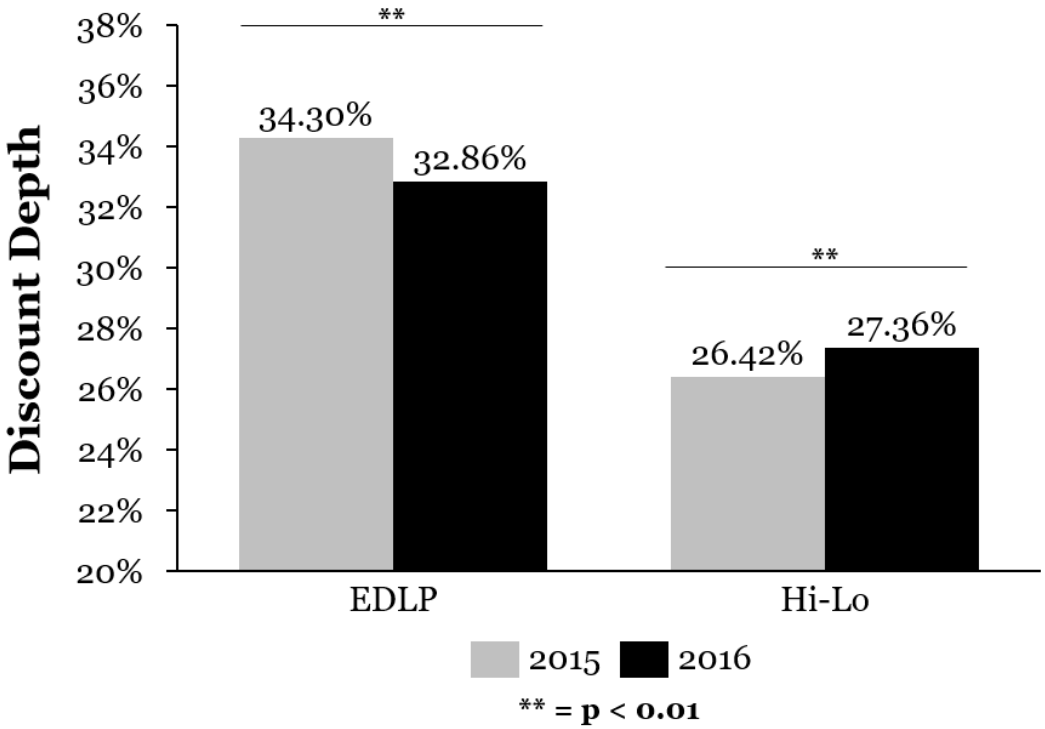


Figure C-2. Mean discount depth development of EDLP and Hi-Lo retailers between 2015 and 2016.

2.4. Discussion

In Study 1 we can observe that retailers, independent of their main pricing strategy, significantly increased the number of price promotions per calendar week over the period of two years. However, regarding the depth of the discounts, the promotion strategies differ between EDLP and Hi-Lo retailers. The results show that, in the future, the differentiation between EDLP and Hi-Lo retailers (e.g, Bell & Lattin, 1998; Fassnacht & El Husseini, 2013) may be diluted, as EDLPs started offering an increasing number of discounts at high discount depths. Thus, we may see an alignment of pricing and promotion strategies. In the following chapter we seek to analyze which of the observed strategies may be more beneficial for retailers by including the consumers' perspective. In doing so, Study 2 analyzes how both discount depth and number of discounted products influence consumers' perception of a store's price image.

3. Study 2: Online Experiment on the Consumer Perception of Discount Strategies

3.1. Conceptual Background

Today, consumers often combine online and offline channels in their customer journey and engage in strategies known as "webrooming", "web-to-store" or "research-shopping" (Flavián, Gurrea, & Orús, 2020; Kleinlercher, Emrich, Dennis, Verhoef, & Rudolph, 2018; Pauwels, Leeflang, Teerling, & Huizingh, 2011; Verhoef, Kannan, & Inman, 2015). A popular part of this strategy is to evaluate prices on price comparison sites (PCS) (Bodur et al., 2015; Jung et al., 2014). PCS are known to influence consumers even in the offline context by shaping their reference price and, thus, altering the perceived attractiveness of offline offers (Bodur et al., 2015). Without consulting their technical devices for price information, consumers often do not know the explicit price of a product (Dickson & Sawyer, 1990; Jensen & Grunert, 2014; Scheidegger, Rudolph, & Linzmajer, 2018; Vanhuele & Drèze, 2002). Therefore, they tend to judge prices intuitively against an internal reference price or they look for simple cues, such as price discounts, while evaluating the attractiveness of the offer (e.g., Inman, Peter, & Raghubir, 1997; Jensen & Grunert, 2014; Monroe, Powell, & Choudhury, 1986). Overall, the prices and perceived attractiveness of the offers shape a consumers' store price image (Alba et al., 1999; Graciola, De Toni, de Lima, & Milan, 2018; Lourenço, Gijsbrechts, & Paap, 2015; Ofir, Raghubir, Brosh, Monroe, & Heiman, 2008) and, thus, influence their store choice and repurchase intention (e.g., Graciola et al., 2018). Because consumers often lack explicit price knowledge (e.g., Jensen & Grunert, 2014; Urbany & Dickson, 1991; Vanhuele & Drèze, 2002) and will get more "low price cues", if more items are on promotion, we hypothesize:

H1: In discount strategies, the number of items on discount will have a higher positive effect on store price image than discount depth.

We expect that previous price research and a consumers' individual price consciousness will influence how the price strategy is perceived and evaluated (store price image). Price consciousness is known to be an influential moderator of price information processing (e.g., Alford & Biswas, 2002; Bozkurt & Gligor, 2019; Kukar-Kinney, Walters, & MacKenzie, 2007; Noh, Lee, Kim, & Garrison, 2013; O'Neill & Lambert, 2001; Scheidegger et al., 2018). An individuals' reaction to price information strongly depends on the subjective importance of prices. Hence, we expect that consumers with a strong fixation on prices react more positively to deeper and/or more frequent discounts than consumers with low levels of price consciousness.

However, we hypothesize, that only when consumers "overvalue" discount cues during their store price image formation (e.g., due to the lack of explicit price knowledge or an emotional/intuitive response to the price discount), the number and depth of discounts will be of significant influence. At this point, PCS may play a crucial role: as the price comparison task may activate a consumer's cognitive system, consumers might reconsider the attractiveness of a discount based on that activation. Alter, Oppenheimer, Epley and Eyre (2007) have shown that, based on experiential cues, people activate their cognitive system because they feel that a simplified System 1 (emotional, quick and intuitive) judgement could lead to a wrong conclusion (see Kahneman (2002) for more information on System 1 and 2). Even if conducted for an unrelated product group, we see a price comparison task as such an experiential cue. We summarize this expected relationship in Hypothesis 2 (see Figure C-3):

H2: The relationship between the retailers' discount strategy (number of discounted products and discount depth) and store price image is dependent on high price consciousness and lack of previous online price research.

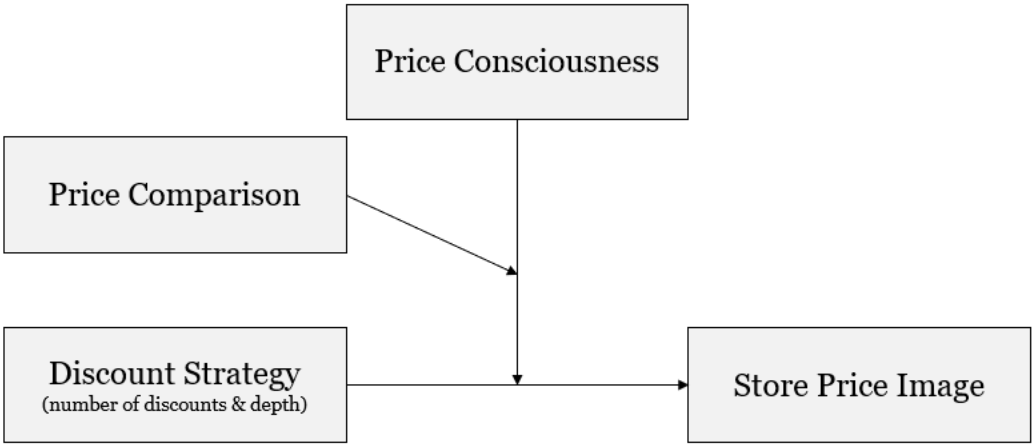


Figure C-3. Conceptual diagram of the hypothesized moderated moderation model.

3.2. Method

To complement the findings of Study 1 with actionable insights, we try to observe the effect of different promotion strategies on store price image in this online experiment. In addition, we analyze the role of PCS and price consciousness. We do this by manipulating the two main determinants of price promotion strategies*: (1) discount depth in %* and *(2) number of discounts offered* at a retailer. 498 U.S.-citizens were recruited on Amazon Mechanical Turk for this study. We excluded participants failing[2] to do the price comparison task (N = 21), leaving a final sample of 477 participants (median age = 33 years; 52.6 % male). To study the hypothesized relationships between price comparison behavior, price consciousness, store price image and discount strategies, the participants were randomly assigned to one of eight experimental groups in a 2 (price comparison manipulation vs. no manipulation) x 2 (20 % discount vs. 40 % discount) x 2 (2 discounted items vs. 4 discounted items) between-subjects design.

First, half of the participants received the task to search for the lowest price of two items, "Gopro Hero 7" and "Apple TV 4K" on Google's price comparison website "Google Shopping". The participants were then asked to state the lowest market prices of the two items in USD. The second part of the study consisted of a grocery-shopping scenario at a fictitious brick-and-mortar retailer "Pine Market". All the participants saw ten everyday items (such as cereals, bread, milk, detergent, eggs etc.) and were asked to put them into their fictitious shopping basket by selecting the items with a click. Pictures and descriptions of the products were deliberately kept neutral to avoid explicit a priori price expectations (see Figure C-4).

In order to ensure plausible purchase prices in our shopping scenario, we priced the items according to best-sellers of the same category on Walmart.com and Amazon Fresh. The items and purchase prices were the same across all conditions and the displayed order of the ten items was randomized during the experiment. However, the number of discounted items (2 vs. 4) as well as the discount depth (20 % vs. 40 %) varied across the four conditions. To increase the external validity of our experiment and to ensure the comparability between Study 1 and Study 2, we used the discounts levels based on the observations in Study 1, where most observations fell between approx. 20 and 40 %. For the sake of comparability between the two factors (depth and number of discounts) we adjusted the number of discounts (2 vs. 4) in the same ratio as the discount depth (20 % vs. 40 %). When an item was on price promotion, only the "before" price was adapted, while the purchase price (price after subtracting

[2] All participants who entered extreme values after the price comparison task. All values 1.5 Inter Quartile Range (IQR) above the 75 %-quartile and 1.5 IQR below the 25 %-quartile were considered as extreme values.

the discount) and therefore the overall basket size was kept constant across all conditions. In doing so, we avoided that the overall basket size would have an effect on store price image rather than the discount strategy (e.g., Desai & Talukdar, 2003).

In fact, the participants would all see and pay the same prices across all scenarios. The discounts would therefore not save them money. Figure C-4 illustrates how two different items varied across the four price promotion conditions. "Strawberry cereals" and "soda cans" were only promoted in 4-discount scenarios and "potato chips" and "liquid laundry detergent" were promoted in all scenarios. We chose those four items as our promotion items as they are frequently discounted at real retail stores. All other items had the same price communication in all scenarios.

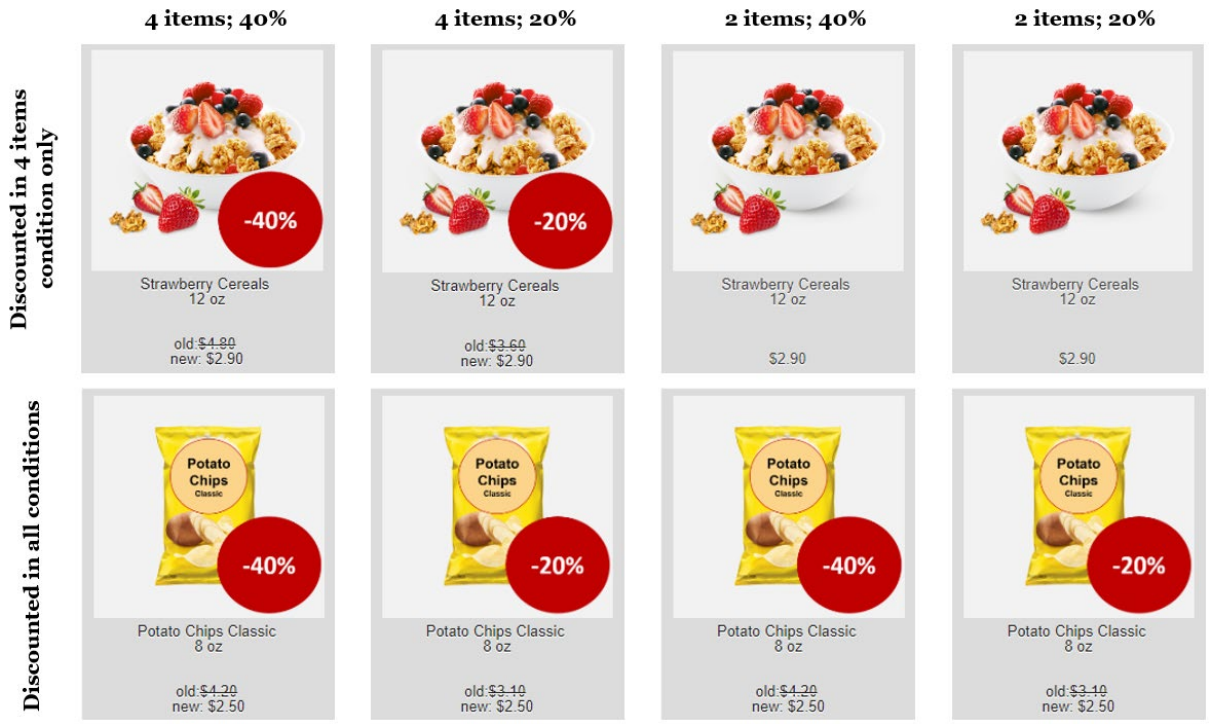


Figure C-4. Two products across the 4 different price discount scenarios (4 items and 40%; 4 items and 20%; 2 items and 40%; 2 items and 20%).

After the product presentation, we measured the participants' perceived store price image of "Pine market" as well as their price consciousness levels. Store price image was measured using a 3-item, 7-point semantic differential (unattractive prices – attractive prices; unreasonable prices for value – reasonable prices for value; prices much lower than other stores – prices much higher than other stores (reverse coded)) developed by Biswas, Pullig, Yagci, and Dean (2002) who adapted the retail store image scale by Dickson and Albaum (1977). Price consciousness (Lichtenstein, Ridgway, & Netemeyer, 1993) values were collected with a 5-item, 7-point Likert scale anchored by totally disagree (1) and totally agree (7): (I am not willing to go to extra effort to find lower prices. (reverse coded); I will grocery shop at more

than one store to take advantage of low prices.; The money saved by finding low prices is usually not worth the time and effort. (reverse coded); I would never shop at more than one store to find low prices. (reverse coded); The time it takes to find low prices is usually not worth the effort. (reverse coded)).

3.3. Results

3.3.1. Effect of Discount Strategy on Store Price Image

As we hypothesize in H1 that the number of discounted products would have a stronger positive effect on store price image (Cronbach`s $\alpha = 0.83$)[3] than the discount depth, we conducted a univariate analysis of variances for discount depth and number of discounts on store price image. While the overall model was significant ($F(3, 474) = 3.01$, $R^2 = 0.02$, $p < 0.05$), only the number of discounts had a significant effect on store price image ($F(1, 476) = 7.34$, $p < 0.05$). On the other hand, discount depth ($F(1, 476) = 0.02$, $p > 0.1$) and the interaction term ($F(1, 476) = 1.56$, $p > 0.1$) had no significant effect on store price image. When comparing the mean store price image values across the four price promotion conditions, only discounts with a high depth showed a significant increase in store price image values with increasing numbers of discounted items (see Figure C-5): At a deep discount level (40 %), store price image values were significantly lower ($t(240) = -2.78$, $p < 0.05$) in the two-discounts condition ($M = 4.54$, $SE = 0.12$) vs. the four-discounts ($M = 5.02$, $SE = 0.12$) condition.

[3] In favor of a high reliability, the reverse coded item had to be removed from the store price image scale.

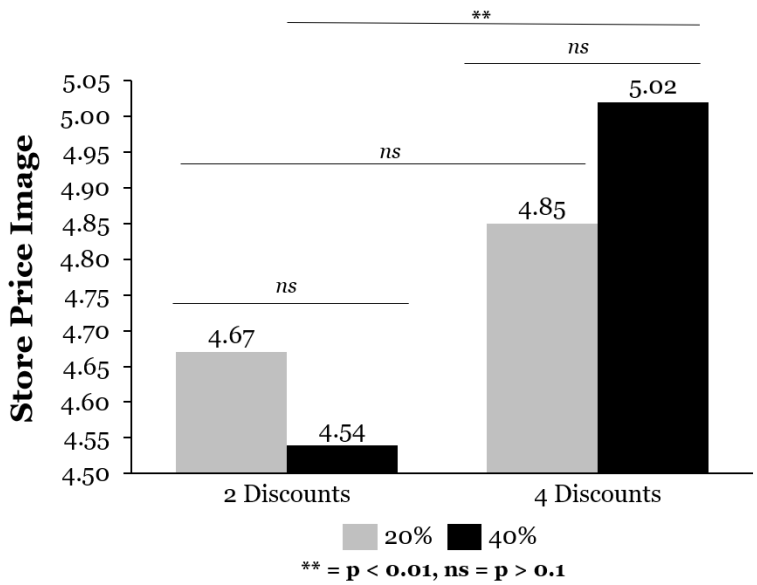


Figure C-5. Store price image values in dependence of discount depth (20% vs. 40%) and number of discounts (2 vs. 4 items).

3.3.2. Moderating Role of Price Comparison and Price Consciousness

To validate our hypothesized moderated moderation model of discount strategy (number of discounted products and discount depth) on store price image in H2, we conducted an analysis using the PROCESS macro for SPSS (Hayes, 2017). Even though discount depth had no significant effect on store price image in the previous analysis, we still tested the moderated moderation model for different discount depths. However, the model (R^2 = 0.02, F(1, 476)=1.56, p > 0.1) and the three-way interaction (p > 0.1) were not significant. We then tested for a significant three-way interaction between number of discounts, price consciousness (Cronbach`s α = 0.84) and price search manipulation and regressed them on store price image. The results are summarized in Table C-1 and indicate a significant three-way interaction as well as a significant overall moderated moderation model.

In a second step, we analyzed the interaction between number of discounts and the main moderator price consciousness at both values of price search manipulation (dummy-coded: 1 = manipulated and 0 = not manipulated). We can observe a significant moderating effect of number of discounts on store price image, when participants have not conducted a price search task (PCSM = 0, effect = 0.13, t = 2.42, p < 0.05). The same effect was not significant in the price manipulation group (PCSM = 1, effect = -0.05, t = -0.67, p > 0.1). We then tried to identify the areas of significant moderated moderation by analyzing the conditional effects of number of discounts on store price image at price consciousness values at ±1 standard deviation from the mean. In Figure C-6 we see a significant moderated moderation

at mean (price consciousness = 4.48, effect = 0.23, t = 3.03, p < 0.05) and high (price consciousness = 6.05, effect = 0.42, t = 3.72, p < 0.05) values of price consciousness. We could not observe a moderated moderation at low values of price consciousness (price consciousness = 3.31, effect = 0.05, t = 0.51, p > 0.1).

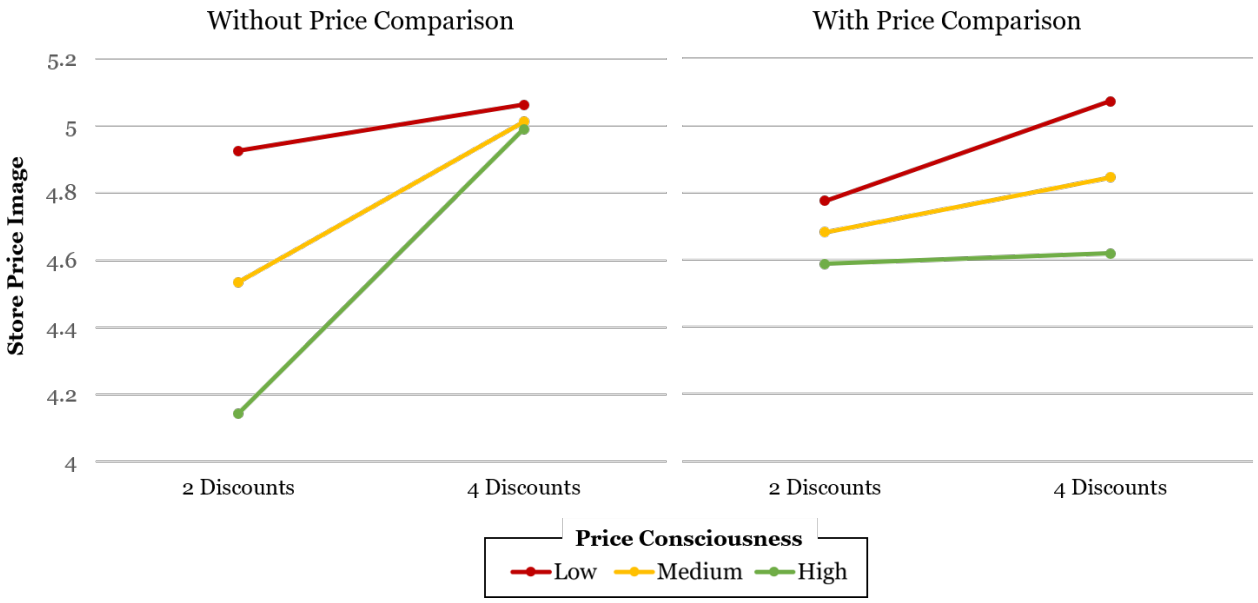


Figure C-6. Moderated moderation between number of discounts and store price image at different values of price consciousness and price comparison.

Table C-1. Moderated moderation summary.

	Coefficient	**SE**	**t**	**p**
Intercept	6.65	0.85	7.85	**
Price Consciousness (PRCN)	-0.56	0.18	-3.14	**
Number of Discounts (NDIS)	-0.39	0.27	-1.47	*ns*
*NDIS*PRCN*	0.13	0.06	2.42	*
PCS Manipulation (PCSM)	-2.27	1.50	-1.52	*ns*
*NDIS*PCSM*	0.70	0.45	1.56	*ns*
*PRCN*PCSM*	0.58	0.30	1.93	†
*NDIS*PRCN*PCSM*	-0.18	0.09	-2.00	*

$R^2 = 0.05$, $F(1, 476) = 3.70$, $p < 0.05$

** = $p < 0.001$; * = $p < 0.05$; † = $p < 0.1$; ns = $p > 0.1$

3.4. Discussion

In Study 2, we find a significant main effect of number of discounts on store price image. At the same time, discount depth did not influence consumers' store price image. We therefore conclude that increasing the number of discounted products may be more beneficial for improving one's store price image than increasing the discount depth. This supports our Hypothesis 1, where we expected that the number of items on discount will have a higher positive effect on store price image than discount depth. However, against our hypothesized effects, discount depth did not have an observable effect on store price image at all. One possible explanation could be that customers classify both 20 % and 40 % as low to moderate discount levels, as they may already have become accustomed to even higher discount depths. We see an alternative possible explanation in consumers' rather low price knowledge. Due to the lack of explicit price knowledge (e.g., Linzmajer, 2013; Scheidegger et al., 2018) consumers may not be able to distinguish between 20 % and 40 % discount depth when they think about how much money they save though the discount.

By bringing the two moderators "price consciousness" and "price comparisons" into our model, we were able to gain even more insights into the relationship between number of discounted products and store price image formation. Conducting an unrelated price comparison task prior to the shopping task erased the positive main effect of number of discounts on store price image. We hypothesize that the price comparison task activates the consumers' cognitive system which will make them less susceptible to discount frames. When the price comparison task was absent, number of discounted products still had a significant effect on store price image. However, this effect was dependent on participants' individual levels of price consciousness. Participants with high levels of price consciousness reacted more strongly to an increased number of discounted products (as illustrated by the steep green slope on the left in Figure C-6). We will further discuss the implications of these and the previous results in the following chapter.

4. General Discussion

Increased price transparency through price comparison websites as well as the ease of gathering price related information has boosted interest in analyzing price discount strategies and consumers' perception of store price image. While preceding research focuses on specific effects of discount strategies on consumer perception and company performance (e.g., Levy, Weitz, & Grewal, 2014), less is known about prevalence and the development of price discount strategies in a competitive retail market. Furthermore, although existing research acknowledges the influence of analyzing smartphone usage in general (Scheidegger et al., 2018), less attention has been given to how the opportunity to compare prices in order to adjust consumers' reference prices affects store price image.

The current research applies the collection of field data to better understand the usage of price discounts in Swiss grocery retailing over time. In combination with an online experiment, we build on recent developments in technology usage by consumers and document the impact of price comparison on store price image. In addition, we also shed light on an important consumer characteristic regarding price perception and decision-making, namely price consciousness.

Our findings make several contributions to the existing literature. First, they inform the ongoing debate about which price discount strategies are used by retailers in a more transparent consumer market. Building from the idea of this increased market price transparency, we measure number of discounts as well as discount depth as central characteristics of price discount strategies. Using the collected promotion data helps us to uncover the development of price discounting activities by Swiss grocery retailers.

Second, our results illustrate that number of discounts and discount depth have different effects on consumers' store price image. Consistent with our theorizing, the number of items on discount have a stronger positive effect on store price image than discount depth. To account for the complex store price image formation with its manifold antecedents, we detail our conceptual model and add the underlying price consciousness of consumers as additional construct. As consumers move through the web, leaving a complex price comparison pattern, the interaction with their price consciousness is a starting point to simplify and structure the antecedents of store price image formation. Relying on extant research into consumer pricing decisions, we transfer the idea of experiential cues into the context of store price image. The store price image of high- and medium price conscious consumers without price comparison activity is strongly influenced by number of discounts. Furthermore, we find no such relationship for low price conscious consumers with price comparison activity. One possible explanation is that price comparison activates the cognitive system of consumers, leading to an adapted judgment of the discount strategy (Alter, Oppenheimer, Epley & Eyre, 2007; Kahneman, 2002).

4.1. Theoretical Implications

This research links retail strategy and psychological approaches to study consumers' store price image. Prior research has used aggregated input measures (such as discount strategy per se), and has also focused on multiple consumer traits (e.g., Ofir et al., 2008). However, none of these studies examines the relationship between discount depth, number of discounts and store price image in a transparent and competitive market. Macro-level outcomes (such as store price image) are dependent on individual micro-level decisions (e.g., using price comparison websites). Thus, when trying to explain the drivers of store price image, emphasis should be placed on consumers' underlying psychological processes. Along these lines, our research suggests that price comparison usage as a proxy for a cognitive activation helps consumers succeed on the path to store price image formation, dependent on their level of price consciousness.

It is also worthwhile to consider these findings in relation to the prevalence and development of price discount strategies. Just as retailers seem to align their price discount strategies moving away from the former EDLP model, their increased use of Hi-Lo principles renders it difficult to distinguish between those two formats. While there was likely some overlap in these determining factors in the past, a clear-cut retailer price discount strategy will constantly dilute in the years to come.

4.2. Practical Implications

These findings also have important practical implications. Faced with the fear of giving away too much or too little discount, retailers align their price discount strategies in competitive and transparent markets. This might lead to a dilution of their former value proposition, making it harder for the company as well as the consumer to identify necessary differentiation characteristics. As price acts as the most important cue for purchase decisions, giving away clear-cut store price images might backfire with regard to company sales and profits. At the same time, our results suggest that increasing the discount depth from 20 % to 40 % did not influence the store price image. Only increasing the number of items on promotion did. We expect that the promotion itself may be a stronger "low price" signal on grocery shoppers than the exact discount depth. This may be due to their lack of explicit price knowledge. Thus, in comparison to discount depth, the increasing number of discounts led to a more favorable store price image. Based on these findings, retailers could save some of their margin by not deepening or even lowering their discount levels. On the other hand, they should focus on providing the consumer with more "low price" signals (e.g., through increasing the number of items on promotion).

Our findings also shed light on the question of drivers of store price image in a digitalized world. As price comparison opportunities will continue to rise, we expect the positive effect of number of discounts on store price image to slowly disappear. When central characteristics of discount strategies do not affect store price image any more, retailers have to rethink current pricing practices: As discounts only reduce the so-called pain of paying, new pricing strategies might focus on emphasizing the reward value of an offer (e.g., Linzmajer, 2013). Interestingly, number of discounts influence highly price conscious consumers to a stronger degree than their price unconscious counterparts. For retailers, this could indicate opportunities to address a group of price specialists with their discount strategy. On the other hand, it becomes increasingly important for consumers to understand the complex mechanisms that lead to their price perceptions in light of an overly complex world with more price cues than ever before. In this respect we show, that if consumers use price comparison opportunities in a digital world, the effects of their general trait of price consciousness on store price image are weakened. We thereby offer an interesting behavioral strategy to manage one's own price consciousness.

4.3. Future Research and Limitations

The data in Study 1 consisted of price discounts on grocery items only. Therefore, we do not know if the observed relationships can be transferred to different product groups (e.g., consumer electronics or fashion). This may be observed through future research.

In general, laboratory experiments lack external validity (e.g., Levitt & List, 2007; Levitt & List, 2008). All participants in Study 2 were not confronted with a real purchase scenario. Therefore, future researchers may try to replicate Study 2 in the field with a collaborating industry partner. Further, we did not adapt the product prices across the different scenarios, in order to control for alternative factors (e.g., basket size). Therefore, we rather observed the effect of discount framing on store price image than the effect of actually saving money.

Through an extension of Study 2, future researchers may be able to differentiate between more levels in "number of discounted products" as well as "discount depth" in order to determine the optimal values. The relationship between a favorable store price image and number of discounted products as well as discount depth may not be linear. In addition, researchers may include (real) brands in their laboratory studies, in order to increase the applicability of these results to an extended range of grocery items.

References

Alba, J. W., Broniarczyk, S. M., Shimp, T. a., & Urbany, J. E. (1994). The Influence of Prior Beliefs, Frequency Cues, and Magnitude Cues on Consumers' Perceptions of Comparative Price Data. *Journal of Consumer Research*, *21*(2), 219. https://doi.org/10.1086/209394

Alba, J. W., Mela, C. F., Shimp, T. A., & Urbany, J. E. (1999). The Effect of Discount Frequency and Depth on Consumer Price Judgments. *Journal of Consumer Research*, *26*(2), 99–114. https://doi.org/10.1086/209553

Alford, B. L., & Biswas, A. (2002). The effects of discount level, price consciousness and sale proneness on consumers ' price perception and behavioral intention. *Journal of Business Research, 55*, 775–783.

Alter, A. L., Oppenheimer, D. M., Epley, N., & Eyre, R. N. (2007). Overcoming Intuition: Metacognitive Difficulty Activates Analytic Reasoning. *Journal of Experimental Psychology: General, 136*(4), 569–576. https://doi.org/10.1037/0096-3445.136.4.569

Bell, D. R., & Lattin, J. M. (1998). Shopping Behavior and Consumer Preference for Store Price Format: Why "Large Basket" Shoppers Prefer EDLP. *Marketing Science, 17*(1), 66–88. https://doi.org/10.1287/mksc.17.1.66

Biswas, A., Pullig, C., Yagci, M. I., & Dean, D. H. (2002). Consumer evaluation of low price guarantees: The moderating role of reference price and store image. *Journal of Consumer Psychology, 12*(2), 107–118. https://doi.org/10.1207/153276602760078640

Blattberg, R. C., & Neslin, S. A. (1989). Sales promotion: The long and the short of it. *Marketing Letters, 1*(1), 81–97. https://doi.org/10.1007/BF00436151

Bliss, C. (1988). A Theory of Retail Pricing. *The Journal of Industrial Economics, 36*(4), 375–391.

Bodur, H. O., Klein, N. M., & Arora, N. (2015). Online Price Search: Impact of Price Comparison Sites on Offline Price Evaluations. *Journal of Retailing, 91*(1), 125–139. https://doi.org/10.1016/J.JRETAI.2014.09.003

Bozkurt, S., & Gligor, D. (2019). Customers' behavioral responses to unfavorable pricing errors: the role of perceived deception, dissatisfaction and price consciousness. *Journal of Consumer Marketing, 36*(6), 760–771. https://doi.org/10.1108/JCM-06-2018-2726

Breuer, R., Brettel, M., & Engelen, A. (2011). Incorporating Long-Term Effects in Determining the Effectiveness of Different Types of Online Advertising. *Marketing Letters, 22*(4), 327–340.

Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013). Competing in the Age of Omnichannel Retailing. *MIT Sloan Management Review, 54*(4), 23–29. https://doi.org/http://dx.doi.org/10.1108/17506200710779521

Cai, F., Bagchi, R., & Gauri, D. K. (2016). Boomerang effects of low price discounts: How low price discounts affect purchase propensity. *Journal of Consumer Research, 42*(5), 804–816. https://doi.org/10.1093/jcr/ucv057

Cao, S. (2019). Yes, shoppers are using search in your store. Here's how to help. https://www.thinkwithgoogle.com/consumer-insights/online-in-store-shopping-search/

Cataluña, F. J. R., Sánchez Franco, M. J., & Villarejo Ramos, A. F. (2005). Are hypermarket prices different from discount store prices? *Journal of Product and Brand Management, 14*(5), 330–337. https://doi.org/10.1108/10610420510616368

Danziger, S., Hadar, L., & Morwitz, V. G. (2014). Retailer Pricing Strategy and Consumer Choice under Price Uncertainty. *Journal of Consumer Research, 41*(3), 761–774. https://doi.org/10.1086/677313

Dekimpe, M, & Geyskens, I. (2019). Using technology to bring online convenience to offline shopping. *Marketing Letters, 31,* 25–29.

Dekimpe, Marnik, Hanssens, D. M., & Silva-Risso, J. M. (1998). Long-run effects of price promotions in scanner markets. *Journal of Econometrics, 89*(1–2), 269–291. https://doi.org/10.1016/S0304-4076(98)00064-5

Dickson, J., & Albaum, G. (1977). A Method for Developing Tailormade Semantic Differentials for Specific Marketing Content Areas. *Journal of Marketing Research, 14*(1), 87–91. https://doi.org/10.2307/3151058

Dickson, P. R., & Sawyer, A. G. (1990). The of Search Knowledge Supermarket Shoppers. *Journal of Marketing, 54*(3), 42–53.

Diehl, K., Kornish, L. J., & Lynch, J. G. (2003). Smart Agents: When Lower Search Costs for Quality Information Increase Price Sensitivity. *Journal of Consumer Research, 30*. https://doi.org/10.2139/ssrn.340040

Falk, T., Kunz, W. H., Schepers, J. J. L., & Mrozek, A. J. (2016). How mobile payment influences the overall store price image. *Journal of Business Research, 69*(7). https://doi.org/10.1016/j.jbusres.2016.01.011

Fassnacht, M., & El Husseini, S. (2013). EDLP versus Hi–Lo pricing strategies in retailing—a state of the art article. *Journal of Business Economics, 83*(3), 259–289. https://doi.org/10.1007/s11573-012-0648-y

Flavián, C., Gurrea, R., & Orús, C. (2020). Combining channels to make smart purchases: The role of webrooming and showrooming. *Journal of Retailing and Consumer Services, 52*, 101923. https://doi.org/10.1016/J.JRETCONSER.2019.101923

Gallagher, K., Foster, K. D., & Parsons, J. (2001). The Medium Is Not the Message: Advertising Effectiveness and Content Evaluation in Print and on the Web. *Journal of Advertising Research, 41*(4), 57–70.

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. https://doi.org/10.1016/J.JRETAI.2017.06.001

Graciola, A. P., De Toni, D., de Lima, V. Z., & Milan, G. S. (2018). Does price sensitivity and price level influence store price image and repurchase intention in retail markets? *Journal of Retailing and Consumer Services, 44*, 201–213. https://doi.org/10.1016/J.JRETCONSER.2018.06.014

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. https://doi.org/978-1-60918-230-4

Heil, O. P., & Helsen, K. (2001). Toward an understanding of price wars: Their nature and how they erupt. *International Journal of Research in Marketing, 18*(1–2), 83–98. https://doi.org/10.1016/S0167-8116(01)00033-7

Hoch, S. J., Drèze, X., & Purk, M. E. (1994). EDLP, Hi-Lo, and margin arithmetic. *Journal of Marketing, 58*(4), 16. https://doi.org/10.2307/1251913

Ilfeld, J. S., & Winer, R. S. (2002). Generating Website Traffic. *Journal of Advertising Research, 42*(5), 49–61.

Inman, J. J., Peter, A. C., & Raghubir, P. (1997). Framing the Deal: The Role of Restrictions in Accentuating Deal Value. *Journal of Consumer Research, 24*(1), 68–79. https://doi.org/10.1086/209494

Jensen, B. B., & Grunert, K. G. (2014). Price knowledge during grocery shopping: What we learn and what we forget. *Journal of Retailing, 90*(3), 332–346. https://doi.org/10.1016/j.jretai.2014.01.001

Jung, K., Cho, Y. C., & Lee, S. (2014). Online shoppers' response to price comparison sites. *Journal of Business Research, 67*(10), 2079–2087. https://doi.org/10.1016/J.JBUSRES.2014.04.016

Kahneman, D. (2002). Prize Lecture: Maps of Bounded Rationality: A Perspective on Intuitive Judgment and Choice. Princeton University.

Kalwani, A. U., & Yim, C. K. (1992). Consumer Price and Promotion Expectations: An Experimental Study. *Journal of Marketing Research, 29*(1), 90–100. https://doi.org/10.2307/3172495

Kaul, A., & Wittink, D. R. (1995). Empirical Generalizations about the Impact of Advertising on Price Sensitivity and Price. *Marketing Science, 4*(3), 151–160.

Kleinlercher, K., Emrich, O., Dennis, H., Verhoef, P. C., & Rudolph, T. (2018). Websites as Information Hubs – How Informational Channel Integration and Shopping Benefit Density Interact in Steering Customers to the Physical Store Journal of the Association for Consumer Research. *Journal of the Association for Consumer Research, 3*(3), 330–342.

Kukar-Kinney, M., Walters, R. G., & MacKenzie, S. B. (2007). Consumer responses to characteristics of price-matching guarantees: The moderating role of price consciousness. *Journal of Retailing, 83*(2), 211–221. https://doi.org/10.1016/j.jretai.2006.01.001

Lal, R., & Rao, R. (1997). Supermarket Competition: The Case of Every Day Low Pricing. *Marketing Science, 16*(1), 60–80.

Lebensmittel Zeitung. (2018). Top 50: Lebensmittelhandel Europa 2018.

Levitt, S. and J. A. List. (2007). Viewpoint: On the Generalizability of Lab Behaviour to the Field. *Canadian Journal of Economics 40*(2): 347–370.

Levitt, S. and J. A. List. (2008). Homo Economicus Evolves. *Science 319*(5865): 909–910.

Levy, M., Weitz, B. A., & Grewal, D. (2014). Retailing Management (9th ed.). New York: McGraw-Hill.

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.

Lidl. (2019). Unsere Angebote diese Woche: Billiger. https://www.lidl.de/de/angebote

Linzmajer, M. (2013). Neuropricing – Ein Beitrag zur Integration der Consumer Neuroscience in die verhaltenswissenschaftlich orientierte Preisforschung und das betriebliche Preismanagement. Bamberg: Difo-Druck GmbH.

Lourenço, C. J. S., Gijsbrechts, E., & Paap, R. (2015). The Impact of Category Prices on Store Price Image Formation: An Empirical Analysis. *Journal of Marketing Research, 52*(2), 200–216. https://doi.org/10.1509/jmr.11.0536

Mela, C. F., Gupta, S., & Lehmann, D. R. (1997). The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. *Journal of Marketing Research, 34*(2), 248–261. https://doi.org/10.2307/3151862

Monroe, K. B., Powell, C. P., & Choudhury, P. K. (1986). Recall versus recognition as a measure of price awareness. *Advances in Consumer Research, 13*, 594–599.

Mulhern, F. J., & Leone, R. P. (1990). Retail promotional advertising: Do the number of deal items and size of deal discounts affect store performance? *Journal of Business Research, 21*(3), 473–487.

Noh, M., Lee, K., Kim, S., & Garrison, G. (2013). Effects of collectivism on actual s-commerce use and the moderating effect of price consciousness. *Journal of Electronic Commerce Research, 14*(3), 244–260.

O'Neill, R., & Lambert, D. (2001). The Emotional Side of Price. *Psychology & Marketing, 18*(3), 217–237.

Ofir, C., Raghubir, P., Brosh, G., Monroe, K. B., & Heiman, A. (2008). Memory-Based Store Price Judgments: The Role of Knowledge and Shopping Experience. *Journal of Retailing, 84*(4), 414–423. https://doi.org/10.1016/j.jretai.2008.08.001

Pauwels, K., Hanssens, D. M., & Siddarth, S. (2002). The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity. *Journal of Marketing Research, 39*(4), 421–439. https://doi.org/10.1509/jmkr.39.4.421.19114

Pauwels, K., Leeflang, P. S. H., Teerling, M. L., & Huizingh, K. R. E. (2011). Does Online Information Drive Offline Revenues?: Only for Specific Products and Consumer Segments! *Journal of Retailing, 87*(1), 1–17. https://doi.org/10.1016/J.JRETAI.2010.10.001

Scheidegger, G., Rudolph, T., & Linzmajer, M. (2018). Smartphone Effect on Shoppers: How Mobile Information Storage Influences Price Knowledge. *European Marketing Academy 47th Annual Conference.*

Sherman, L., & Deighton, J. (2001). Banner Advertising: Measuring Effectiveness and Optimizing Placement. *Journal of Interactive Marketing, 15*(2), 60–64. https://doi.org/10.1002/dir.1011

Tellis, G. J., & Franses, P. H. (2006). Optimal Data Interval for Estimating Advertising Response. *Marketing Science, 25*(3), 217–229. https://doi.org/10.1287/mksc.1050.0178

Urbany, J. E., & Dickson, P. R. (1991). Consumer Normal Price Estimation: Market versus Personal Standards. *Journal of Consumer Research, 18*(1), 45. https://doi.org/10.1086/209239

van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. *Marketing Letters, 24*(4), 339–351. https://doi.org/10.1007/s11002-012-9222-1

Vanhuele, M., & Drèze, X. (2002). Measuring the Price Knowledge Shoppers Bring to the Store. *Journal of Marketing, 66*(4), 72–85. https://doi.org/10.1509/jmkg.66.4.72.18516

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing. *Journal of Retailing, 91*(2), 174–181. https://doi.org/10.1016/J.JRETAI.2015.02.005

Walters, R. G., & MacKenzie, S. B. (1988). A structural equations analysis of the impact of price promotions on store performance. *Journal of Marketing Research, 25*(1), 51–63. https://doi.org/10.2307/3172924

D. ESSAY III

Scheidegger, G. (submitted). “35 Candy for a T-Shirt?”: How a Currency’s Dissimilarity to Money Decreases Purchase Intentions. *Psychology & Marketing.*

“35 Candy for a T-Shirt?”: How a Currency’s Dissimilarity to Money Decreases Purchase Intentions

Abstract

Money is much more than dollars, pounds or yen. The digitization of money has led to the emergence of numerous fantasy currencies (i.e., company-issued currencies for purchases within the company’s ecosystem). Billions of US dollars are exchanged using such fantasy currencies every year. Still, most pricing-related research focuses on payments using official currencies. In our article, we build upon payment mechanism and processing fluency research to predict consumers’ purchase intentions with fantasy currencies. Study 1 addresses how perceived money similarity can be predicted by semantic similarity measurements. In Studies 2 and 3, we replicate real-world purchase scenarios to show how a fantasy currency’s dissimilarity to money decreases purchase intentions through both the decrease of processing fluency and the increase of pain of payment. Managerial as well as theoretical implications are discussed.

1. Introduction

When one considers money, one's home country currency often comes to mind first: Dollars ($) in the US, pounds (£) in the UK, yen (¥) in Japan, and so on. Yet economic theory defines money much more broadly by three basic functions: (1) medium of exchange, or as an intermediary between buyer and seller; (2) store of value, or retaining its function (i.e., purchasing power) over time; and (3) unit of account, or measuring the value of a product or service against it (Mankiw, 2007). Everything that fulfills these functions can be considered money: Poker chips, cryptocurrencies such as Bitcoins, credits for an online store, 'Gems' and 'Coins' in mobile gaming apps, and many more.

Businesses all over the globe generate substantial revenue with these alternative currencies, which are termed 'fantasy currencies' in this article. We define fantasy currencies as company-issued currencies for purchases within the company's ecosystem. Game developers in particular entice players to exchange regular money (e.g., US dollars) into fantasy currencies such as 'Chocolate Bars' (in Candy Crush) or 'Gems' (in Clash of Clans) to pay for in-game purchases. Fortnite, a free-to-play online game, generated over $1 billion in revenue over the last two years on its mobile version alone (Sensor Tower, 2020a). Pokémon Go, another free-to-play online game, exceeded a lifetime revenue of $3.6 billion this year, four years after it was introduced (Sensor Tower, 2020b). All of these $4.6 billion of payments have been made in V-Bucks (Fortnite) and PokéCoins (Pokémon Go). To put these numbers into perspective, in 2020, the total available funds of the UN Refugee Agency (UNHCR), which serves 79.5 million forcibly displaced people worldwide, were $4.6 billion as well (UNHCR, 2020a, 2020b).

Fantasy currencies can also be found outside the gaming world. For example, two major Swiss retailers with a combined revenue of $66.8 billion reward loyal customers with 'Superpoints' (Coop, 2020) or 'Cumulus Points' (Migros, 2020) that can be used for purchases at their stores. Numerous large-scale events, such as Coachella and Tomorrowland – two of the world's biggest music festivals – have switched to cashless payments in the past few years (Forbes, 2020; Tomorrowland, 2020), and some of these have taken the opportunity to introduce a fantasy currency. For example, all payments at Tomorrowland are made with Pearls (1 Pearl = €1.6).

Despite their financial relevance and increasing popularity, fantasy currencies are an understudied subject in marketing research. Thus, this article seeks to understand how these fantasy currencies may affect consumers' purchase intentions and why. We build upon payment mechanism and processing fluency literature to systematically uncover the underlying psychological processes in two real-life-inspired purchase scenarios.

There is strong consensus in payment mechanism research that dissimilarity between a form of payment and money decreases the negative feelings associated with a purchase (e.g., Gafeeva et al., 2018; Soman, 2003; Thomas et al., 2011; White, 2008). Based on recent findings with regard to processing fluency (Motyka et al., 2016), we argue that this is not the case for payments with fantasy currencies. In fact, we believe that the direction of the relationship between money similarity and pain of payment is reversed in this context. In addition, we seek a free and easy-to-use tool to predict how a fantasy currency's name may influence perceived money similarity. Our findings hold important managerial and theoretical implications and may encourage future research on this matter.

2. Theoretical Background

How consumers pay for a product or a service (payment mechanism) can significantly influence their purchase behavior. Previous research has shown that the chosen payment method can have a considerable influence on factors such as purchase amount, price recall, purchase intention, or product choice (Gafeeva et al., 2018; Raghubir & Srivastava, 2008; Soman, 2003; Thomas et al., 2011; White, 2008). These results are robust over a variety of analyzed payment mechanisms: credit cards (Raghubir & Srivastava, 2008; Soman, 2003; Thomas et al., 2011), gift cards (White, 2008), stored value cards (Soman, 2003), or smart cards (Gafeeva et al., 2018).

Soman (2003) ranked different payment mechanisms based on their perceptual similarity to cash payments. He termed this similarity "payment transparency," where a high payment transparency corresponds to a high similarity to cash payments. Payment transparency is a popular explanation for the observed differences in consumer responses to different payment mechanisms (e.g., Gafeeva et al., 2018; Raghubir & Srivastava, 2008). During a series of interviews, Soman (2003) found that, among other factors, payment transparency is influenced by the salience of a payment mechanism's form. For example, spending money in cash is very salient as one can see and actually feel the money being spent (Soman, 2003). Conversely, alternative payment mechanisms (e.g., credit cards) reduce this salience by making the outflow of money less tangible (Raghubir & Srivastava, 2008). Instead of physically handing over coins and bills to a cashier, a plastic card is simply held against a reader—a frictionless process that reduces consumers' pain of payment and the way they process their spending.

Pain of payment describes individuals' general reluctance to spend money and the associated negative feelings (Zellermayer, 1996). Reducing payment transparency can lower these negative feelings that discourage consumers from consuming (Raghubir & Srivastava, 2008). In other words, lowering pain of payment through the reduction of payment transparency increases consumption (Prelec & Loewenstein, 1998). Therefore, many researchers who

have studied the effects of payment transparency on relevant outcome variables (e.g., purchase intention or product choice) have considered pain of payment as describing the underlying psychological process (Prelec & Loewenstein, 1998; Raghubir & Srivastava, 2008; Thomas et al., 2011; Zellermayer, 1996).

Raghubir and Srivastava (2008, p. 214) compared non-transparent payment mechanisms to paying with "play or monopoly money" due to their intangibility. This analogy illustrates how a reduction in transparency may ultimately lead to people not being aware of spending real money at all. However, if consumers actually pay with play or monopoly money or another non-existing currency (i.e., fantasy currency) after exchanging real money into the fantasy currency and then using this for subsequent purchases, the dynamic may change. Based on previous research in payment transparency as well as Raghubir and Srivastava's (2008) example, one could expect that purchases with fantasy currencies are less transparent and would thus reduce pain associated with the purchase.

Alternatively, considering payment mechanisms and their transparency, a change of currency could also be regarded as an unconventional form of price framing (Raghubir et al., 2012). In fact, payment transparency does not acknowledge how a completely unfamiliar payment form may influence a consumer's ease of processing this price information (i.e., processing fluency). Previous research suggests that processing fluency plays a vital role during the purchase process (e.g., Alter & Oppenheimer, 2008; Chang, 2013; Motyka et al., 2016). Processing fluency depends on numerous factors such as the format of available price information (Motyka et al., 2016) and available payment forms (Alter & Oppenheimer, 2008; Mishra et al., 2006). Alter and Oppenheimer (2008) demonstrated that consumers who paid with unfamiliar and therefore less fluent forms of currency (e.g., a rare and unfamiliar coin or a $2 bill) believed they possessed less purchasing power than consumers who paid with familiar forms of currency (e.g., a $1 bill). In addition, prices presented in a disfluent format require more processing efforts from consumers (Motyka et al., 2016).

Deeper processing of price information alters consumers' purchase decisions because consumers place more emphasis on the price itself (Motyka et al., 2016). Motyka et al. (2016), showing that disfluent prices increase purchase intentions even in the context of price promotions. Conversely, disfluent prices decrease purchase intentions when price information is less favorable (e.g., regular or higher price). In line with this argument, we expect disfluent payments with fantasy currencies to increase consumers' focus on cost of purchase (i.e., price). Consumers express this higher cost focus by displaying higher levels of pain of payment (Raghubir & Srivastava, 2008). Therefore, we hypothesize,

Hypothesis 1: (a) Payments with fantasy currencies negatively influence consumers' purchase intentions. This process is serially mediated by (b) a decreasing processing fluency and (c) an increasing pain of payment.

App developers, retailers, or service providers can name their virtual fantasy currency anything: "Coins," "Diamonds," "Candies," "Chocolates," or "Pearls." Importantly, choice of name alone may have consequences on the hypothesized psychological process. Some currency names share a high semantic similarity with the concept of money (e.g., "Coins") while others differ substantially (e.g., "Candies"). Researchers have shown that semantic similarities between words or concepts enhance processing fluency (Labroo et al., 2008; Whittlesea, 1993). For example, Labroo et al. (2008) argued that, due to a higher processing fluency, liking of a wine increases when the label shows an image which is semantically related to the concept of wine compared to a semantically unrelated image. Based on these findings, we hypothesize the following:

Hypothesis 2: Consumers' processing of price information displayed in a fantasy currency is dependent on the fantasy currency's semantic similarity to money. A lower semantic similarity to money will lead to a decrease in processing fluency.

We address these hypotheses with our empirical package consisting of three studies. In Study 1, we test the connection between objectively calculatable semantic money similarity and consumers' perceived money similarity. Study 2 tests how different fantasy currencies influence pain of payment and purchase intention. Study 3 extends the mediation model tested in Study 2 and introduces processing fluency as a potential second mediator.

3. Study 1: Predicting Perceived Money Similarity of Fantasy Currencies Through Semantic Similarity

Study 1 addresses Hypothesis 2 and aims to find an objective predictor of consumer perceptions of money similarity with different fantasy currencies. By using a large lexical database as well as an online survey, we determined whether semantic money similarity can predict perceived money similarity for consumers. We further used these results to design the subsequent studies analyzing the underlying psychological process based on the mediators pain of payment and processing fluency.

3.1. Method

In a first step, we calculated semantic similarity between different popular fantasy currencies (*Coins*, *Diamonds*, *Gems*, *Gold*, and *Candy*)[1] and the word *money*. Based on WordNet (Princeton University, 2010), a lexical database for semantic relationships between words, we quantified the similarities using a well-established semantic similarity measure (Wu & Palmer, 1994).[2] As visualized in Figure D-1, the currencies studied differed in their semantic similarity to the word *money*. Coins showed the highest (.841) and candy the lowest (.222) Wu-Palmer-measure (WUP) values; the measure ranges from 0 (no semantic similarity) to 1 (perfect semantic similarity).

In a second step, we surveyed one hundred and ten U.S.-based participants (median age = 30 years, 58.2% male) on Amazon Mechanical Turk (AMT). Based on best practices for ensuring satisfactory data quality in AMT panels (e.g., Peer et al., 2014), we used an approval rate of 95% and above as the filter criteria.

In our survey, all participants rated the five virtual fantasy currencies (Coins, Diamonds, Gems, Gold, and Candy) according to how similar they felt the currency was to money. For each fantasy currency, participants rated perceived similarity on a 7-point scale from "very different from money" to "very similar to money." Lastly, they were asked to rank the five fantasy currencies from highest to lowest perceived similarity to money.

[1] We chose these five fantasy currencies based on their popularity in the gaming industry as well as their semantic variability (in WUP). For example: Coins and gems are used in 'Clash of Clans' mobile game (over 500 million downloads).

[2] More information on calculating the semantic similarity can be found in the supplements. For more information on WordNet see: https://wordnet.princeton.edu/

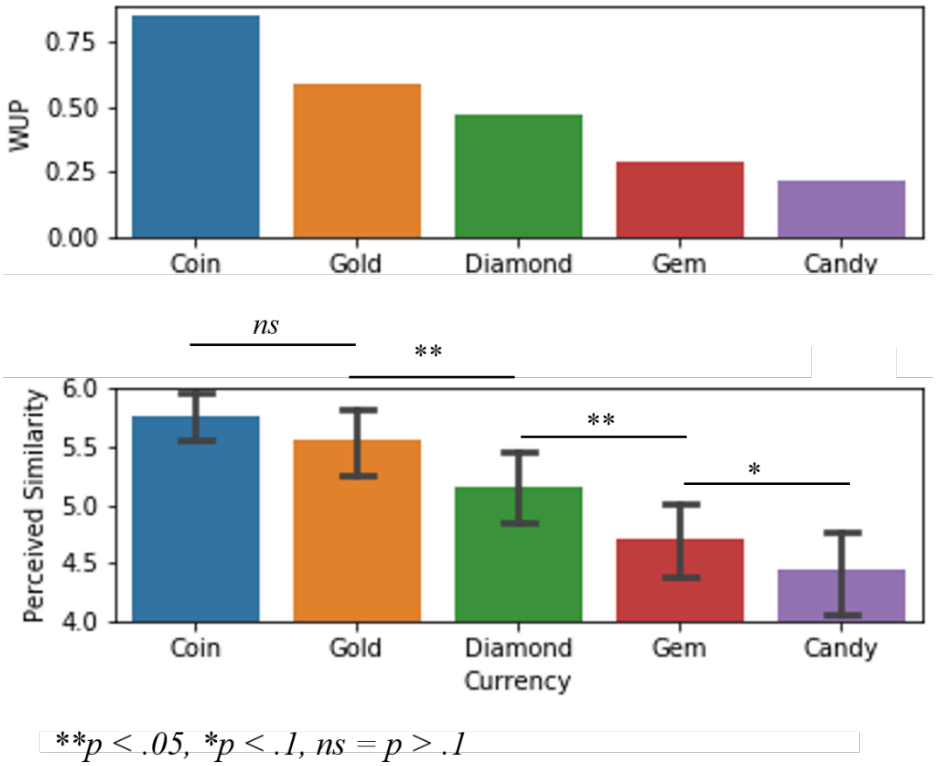


Figure D-1. Top: Semantic similarity between money and different fantasy currencies expressed using the Wu-Palmer-measure (WUP). Bottom: Mean values of perceived similarity (1 = very different from money, 7 = very similar to money) between money and different fantasy currencies based on an Amazon Mechanical Turk survey (N=110).

3.2. Results

An analysis of variance (ANOVA) with repeated measures (with Huynh-Feldt correction due to a violation of sphericity: Mauchly-$W(9) = .640$, $p < .001$, $\varepsilon_{\text{Huynh-Feldt}} = .813$) revealed that similarity perception significantly differed between fantasy currencies ($F(3.253, 354.621) = 21.606$, $p < .001$, partial $\eta^2 = .165$, $n = 110$). In pair-wise comparisons with repeated contrasts, perceived similarity significantly differed between all currencies ($M_{\text{Gold}} = 5.555$ versus $M_{\text{Diamond}} = 5.155$, $F(1, 109) = 7.42$, $p < .05$; $M_{\text{Diamond}} = 5.155$ versus $M_{\text{Gem}} = 4.709$, $F(1, 109) = 7.45$, $p < .05$; $M_{\text{Gem}} = 4.709$ versus $M_{\text{Candy}} = 4.436$, $F(1, 109) = 2.90$, $p < .1$) with the exception of Coin and Gold ($M_{\text{Coin}} = 5.764$ versus $M_{\text{Gold}} = 5.555$, $F(1, 109) = 2.49$, $p = .12$). The effect size according to Cohen's (1988) f was .445, signifying a strong effect. The evaluation of the ranking task corroborated the order of the fantasy currencies' similarity to money. The mode of rankings per fantasy currency was Coin (1 = most similar to money), Gold (2), Diamond (3), Gem (4) and Candy (5= least similar to money).

3.3. Discussion

Study 1 showed significant differences in participants' money similarity perceptions of fantasy currencies. In fact, the reported similarities followed the same order predicted by our semantic similarity calculations (see Figure D-1). Based on these observations, we conclude that semantic similarity was able to predict the order of perceived similarity among study participants. We used these findings to determine appropriate manipulations in Study 2 and Study 3.

4. Study 2: The Relationship Between Perceived Money Similarity, Pain of Payment and Purchase Intentions

Study 2 tested whether the relationship between money similarity, pain of payment, and purchase intentions suggested by payment mechanism research is applicable in the context of fantasy currencies. In this study, we addressed Hypotheses 1a and 1c. In a fictitious event scenario inspired by one of the world's largest music festivals, Tomorrowland, we investigated how perceived money similarity influences purchase intentions through pain of payment. Tomorrowland is a Belgian electronic dance music festival that uses a fantasy currency, Pearls, for purchases on festival grounds (Tomorrowland, 2020).

4.1. Method

Four hundred fifty-three UK-based participants with an approval rate of 95% and higher were recruited on Prolific for this study (median age = 35 years, 64.5% female). We told all participants that they would spend their upcoming holidays in the US and would visit the fictitious "Spring Music Festival" there. They were asked to read an e-mail from the festival organizers informing them about the payment system on the festival grounds. All payments at the festival would be cashless in either dollars (control) or Gold or Candy (fantasy currencies), depending on the experimental scenario. All festivalgoers would need to top up Dollars/Gold/Candy to their festival account before the festival. After they read the e-mail, all participants were redirected to their festival account. We told them (see Figure D-2) that they would have converted 150 Dollars/Gold/Candy for 114.80 pounds (local currency of participants). The currency conversion rate was kept constant among all scenarios and corresponded to the actual conversion rate between dollars and pounds, which was .77 at the time of the study.

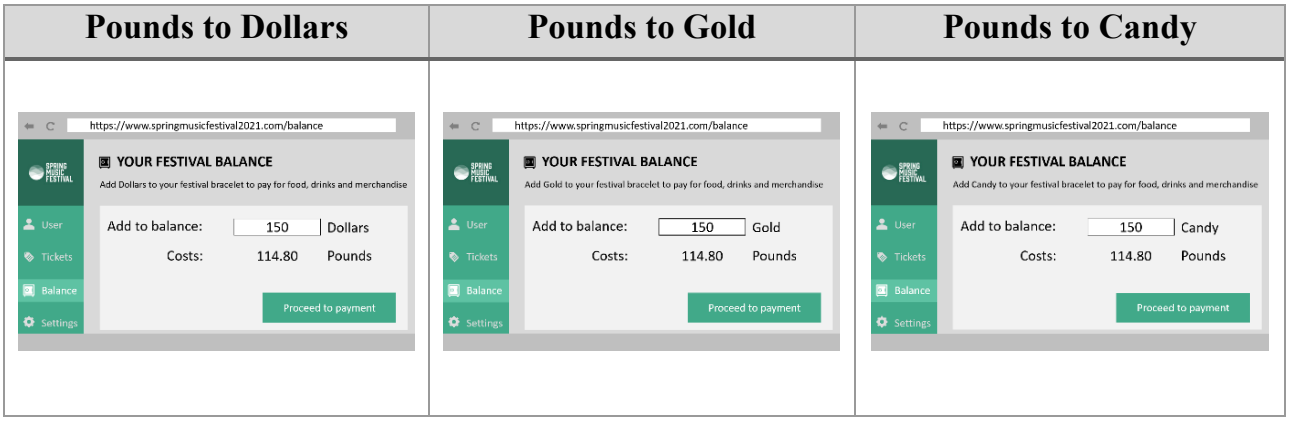


Figure D-2. Stimuli used for all three currency conversion scenarios in Study 2.

In the instructions they read that a few weeks later, they would find themselves at the music festival in front of the festival's merchandise booth. They are interested in the official Spring Music Festival t-shirt and see that it costs 35 Dollars/Gold/Candy.[3] Participants were then asked to indicate their purchase intentions for the t-shirt on a 5-item, 7-point scale by Dodds et al. (1991). After participants were told that they had bought the t-shirt, we measured their pain of payment on a 5-point semantic differential (sad smiley – happy smiley; Thomas et al., 2011). Lastly, they indicated how similar the currency they used for the purchase felt to money on a 7-point semantic differential from (1= very different, 7 = very similar).

4.2. Results

Our currency manipulations were successful. The results of a one-way ANOVA showed that the currency (coded as 1 = Dollars, 2 = Gold, and 3 = Candy) had a significant effect on perceived money similarity ($F(2, 450) = 10.66$, $p < .001$, partial $\eta^2 = .045$). Planned contrasts revealed that the fantasy currencies Gold and Candy scored significantly lower in perceived money similarity than Dollars ($M_{Dollars} = 4.66$ versus $M_{Gold} = 3.85$ and $M_{Candy} = 3.74$; $t(450) = 4.59$, $p < .001$). However perceived money similarity was not significantly different between the two fantasy currencies ($M_{Gold} = 3.85$ versus $M_{Candy} = 3.74$; $t(450) = .51$, $p = .61$).

We tested the hypothesized mediation model (Hypothesis 1a and 1c) with Model 4 from Hayes' (2017) PROCESS macro with 5,000 bootstrapped samples. Perceived similarity was the independent variable, purchase intentions (Cronbach's $\alpha = .958$) the dependent variable, and pain of payment (measured by semantic differential) the mediator. The mediation

[3] We chose this price based on the mode of artist/band t-shit prices. All headliner artists/bands of the popular 'Coachella' festival over the last six years were included in this calculation (N=18).

model was statistically significant ($F(2, 450) = 448.79$, $R^2 = 66.6\%$, $p < .001$). Stronger pain of payment significantly decreased ($b = -.812$, $p < .001$) purchase intentions. At the same time, perceived money similarity significantly decreased ($b = -.159$, $p < .001$) pain of payment without having a direct effect on purchase intentions ($b = .025$, $p = .37$). Overall, the results showed a significant indirect effect of perceived money similarity on purchase intentions ($b = .111$, 95% CI [.040, .182]) while the direct effect was not significant ($b = .025$, 95% CI [-.025, .068]). The entire path diagram is presented in Figure D-3.

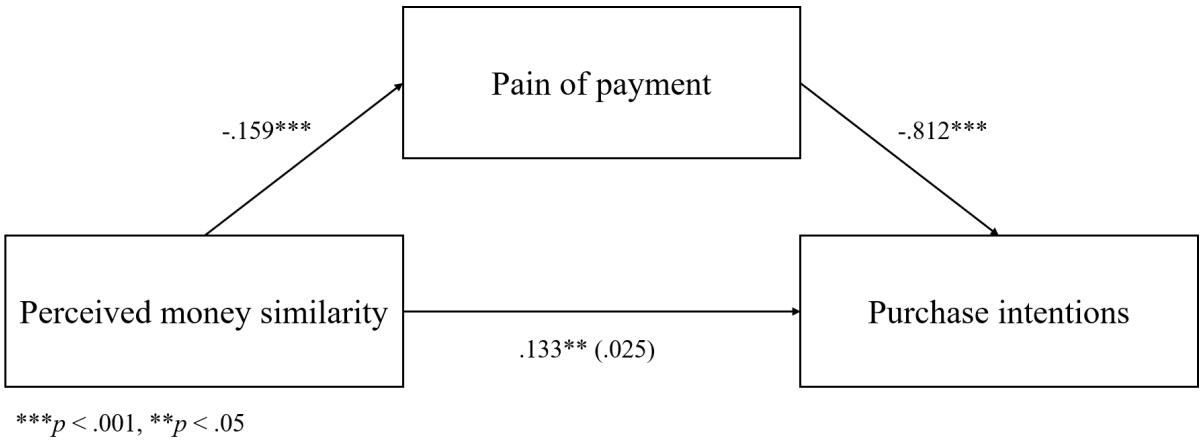


Figure D-3. Path diagram with standardized regression coefficients for the relationship between perceived money similarity and purchase intention as mediated by pain of payment. The standardized regression coefficient between perceived money similarity and purchase intention, controlling for pain of payment, is in parentheses.

4.3. Discussion

The results from the mediation analysis support our hypothesized relationship between perceived money similarity, pain of payment, and purchase intentions. A decrease in perceived money similarity led to an increase in pain of payment. People who experienced a higher pain of payment had lower purchase intentions for the product in the first place. Thus, paying with fantasy currencies may have negative consequences for businesses through the increase in pain of payment. In the next study, we investigated why this negative relationship occurs in the context of fantasy currencies despite contradictory evidence from payment transparency literature in which less similarity to cash payments leads to a decrease in pain of payment.

5. Study 3: The Mediating Role of Processing Fluency

In Study 2, we found that higher similarity with money led to a decrease in pain of payment and an increase in purchase intentions. The aim of Study 3 is to introduce processing fluency as an additional mediator to further explain the counterintuitive negative relationship between perceived money dissimilarity and pain of payment.

5.1. Method

For this study, three hundred and two UK citizens were recruited through Prolific (median age = 33 years, female = 67.9%, task approval rate ≥ 95%). At the beginning of the survey, we introduced participants to the loyalty program of a fictitious grocery retailer 'OakMart.' OakMart was described as having a loyalty program where shoppers would receive a credit of 1 Pound or 1 Acorn, depending on the scenario they were randomly assigned to, for every 100 pounds they spent at OakMart.[4] We chose to use Acorns as a fantasy currency in this shopping scenario due to its low semantic similarity to money (WUP = .211) and suitability to the grocery context. In contrast to candy, acorns cannot be bought at a grocery retailer and thus avoid misunderstandings by study participants.

We told all participants that they had accumulated enough loyalty Pounds (Acorns) to buy groceries at OakMart's online loyalty store. On OakMart's loyalty store, all participants were shown the same 10 everyday grocery items (milk, bread, eggs, cereals, apples, potatoes, laundry detergent, potato chips, soft drinks, and cheese) in random order, and they were asked to put each item in their shopping bag by clicking on it. We included a brief description and price (either Pounds or Acorns) under each item. The participants saw a final balance of 20.93 Pounds/Acorns for the 10 items before we asked them about their purchase intentions (Dodds et al., 1991). They indicated their processing fluency on a single item semantic differential (as suggested by Graf et al., 2018) from 1 = "The process of evaluating the prices on OakMart's online shop was difficult" to 7 = "…easy." We measured pain of payment (Thomas et al., 2011) and perceived money similarity in an identical manner to Study 2.

[4] This conversion rate of 1:100 is used by some retailer's cash-back loyalty programs (e.g., Swiss retailers 'Coop' and 'Migros').

5.2. Results

The currency manipulation was successful. Participants in the Pounds scenario reported a significantly higher money similarity than participants in the Acorns scenario (M_{Pounds} = 5.000 versus M_{Acorns} = 4.054, $t(300) = 4.412$, $p < .001$).

We calculated a serial mediation model (Hayes' (2017) PROCESS macro Model 6 with 5,000 bootstrapped samples) with perceived money similarity as the independent variable and purchase intention as the dependent variable. We integrated processing fluency and pain of payment as serial mediators. The serial mediation model visualized in Figure D-4 was statistically significant ($F(2, 300) = 68.81$, $R^2 = 40.9\%$, $p < .001$). Perceived money similarity had a positive effect on processing fluency ($b = .166$, $p < .05$), which had a negative effect on pain of payment ($b = -.222$, $p < .001$). Replicating the effects from Study 2, pain of payment negatively ($b = -.620$, $p < .001$) influenced purchase intentions (Cronbach's $\alpha = .947$). A significant indirect effect on the serial mediation path was measured (perceived money similarity → processing fluency → pain of payment → purchase intentions; $b = .017$, 95% CI [.004, .035]). The reverse mediation path (perceived money similarity → pain of payment → processing fluency → purchase intentions) was not significant ($b = .000$, 95% CI [-.001, .003]). The direct effects of perceived money similarity on purchase intentions ($b = .006$, $p = .90$) as well as the effect of processing fluency on purchase intentions ($b = .070$, $p = .13$) were not significant. In addition, perceived money similarity did not directly affect pain of payment when controlling for processing fluency ($b = .001$, $p = .99$). These results support our hypothesized serial mediation model (Hypothesis 1a–c).

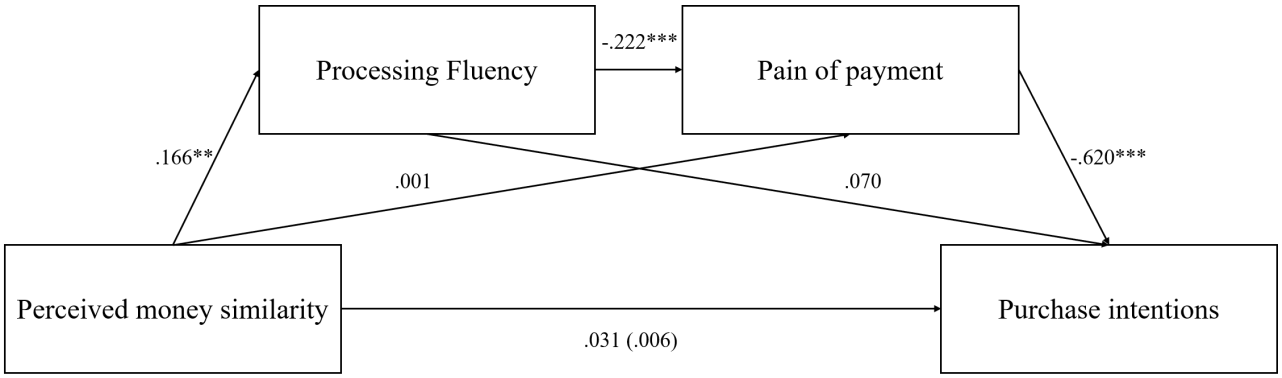


Figure D-4. Path diagram with standardized regression coefficients for the relationship between perceived money similarity and purchase intention as mediated by processing fluency and pain of payment. The standardized regression coefficient between perceived money similarity and purchase intention, controlling for processing fluency and pain of payment, is in parentheses.

5.3. Discussion

In Study 2, we found a positive relationship between perceived money similarity and purchase intentions mediated by pain of payment. In Study 3, we were able to show that this mediation is dependent on a second mediator, namely processing fluency. Including processing fluency as a mediator diminished the direct effect of perceived money similarity on pain of payment. At the same time, the indirect effect of perceived money similarity on purchase intentions was fully mediated by the two mediators. We discuss the theoretical and managerial implications as well as the limitations of these results and those of Studies 1 and 2 in the following section.

6. General Discussion

6.1. Theoretical Implications

To the best of our knowledge, this is the first publication to investigate the use of fantasy currencies in a marketing context. Most research in the field of payment mechanisms focuses on payments with official currencies only. Within the scope of official currencies, researchers have shown that companies may benefit from customers feeling they were spending "play or monopoly money." However, our research shows that this may not be the case if consumers actually pay with fantasy currencies similar to such play money.

In Study 2, we tested the relationship substantiated by payment mechanism research where a lower similarity to money leads to an increase in purchase intentions through the decrease in pain of payment. In the context of fantasy currencies, we were able to show that this relationship does not hold. In fact, purchase intentions decreased with lower money similarity. To explain the underlying psychological process, we introduced processing fluency as a second mediator preceding pain of payment. The relationship was fully mediated and indicated that lower money similarity reduces processing fluency, while pain of payment increases. These results emphasize the importance of considering processing fluency when studying how different payment forms influence consumers' purchase intentions. Furthermore, findings from payment mechanism research may not be applicable when studying fantasy currencies.

6.2. Managerial Implications

The digitization of money has increased the ease of creating fantasy currencies for business purposes. Today, numerous companies use digital currencies for loyalty programs, payments at events, or within console or mobile games. Practitioners may be tempted to choose a currency name that does not remind their customers of spending actual money or to name their fantasy currency in accordance with their brand name or image. For example, the Tomorrowland music festival uses Pearls as its fantasy currency to match the fairytale theme of the festival. However, our results show that this practice may be counterproductive and potentially leads to a decrease in purchase intentions. In Study 3, we deliberately chose a currency name (Acorns) that connects well with the fictitious retailer brand OakMart. Despite our attempt to match the retailer name and the fantasy currency name, we were able to show that fantasy currencies such as Acorns that are low in money similarity led to a decrease in purchase intentions.

We found a significant relationship between semantic money similarity and perceived money similarity (Study 1). As such, companies can easily use WordNet to pretest the semantic similarity of several fantasy currency names that match their internal criteria and choose the name with the highest similarity to money. Even adding a money-related term such as "Coin" or "Cash" to the fantasy currency name (e.g., CandyCoins) could lead to an increase in fluency.

However, in some scenarios, retailers may even benefit from consumers' lower purchase intentions. If a retailer rewards loyal customers with a certain amount of fantasy currency for every dollar they spend at the store (see Study 3), retailers lose money for every product purchased with fantasy currency instead of a regular money. Thus, reducing the consumers' intentions to spend those loyalty funds may even lead to higher profits under certain circumstances.

6.3. Limitations and Future Research

We increased the external validity of our experimental studies using real-life examples. Nevertheless, field data may be necessary to further increase the external validity of our results. Even though the manipulation between fantasy currencies and the control currency was successful in Study 2, we did not find a significant difference between the perceived money similarity of the two fantasy currencies of Candy and Gold. These limitations leave room for future research. Additional studies and stronger manipulations may be needed to further test these differences between fantasy currencies.

Future researchers may want to investigate the impact of fantasy currencies' symbols on processing fluency, pain of payment, and purchase intentions. For example, does "14 🍬" further decrease processing fluency in price evaluations compared to "14 Candy"? Conversely, symbols or pictures may even increase processing fluency (e.g., Labroo et al., 2008) if the symbol itself serves as money prime. Thus, putting a candy symbol on a coin could lead to increased purchase intentions. Although the cryptocurrency bitcoin only exists digitally, it is often depicted as an actual coin with its currency symbol ₿ engraved on top. This may be a way to increase processing fluency for bitcoin purchases and to increase its acceptance as a payment form. In addition, we expect that unfamiliarity with a fantasy currency decreases processing fluency. Therefore, this negative effect might vanish over time after regularly engaging with this form of payment.

AppsFlyer (2016), an analytics company, analyzed 30 million in-app purchases from over 100 apps with a total value of $300 million. They showed that only a fraction of users account for most revenues. In fact, only 3.5% of gamers spent money (AppsFlyer, 2016). To understand the success of in-app spending as the effects of fantasy currencies in general, future researchers may need to consider the characteristics (e.g., personality traits) of heavy users.

In our studies, we kept conversion rates between the fantasy currencies (Acorns and Candy) and control currencies (Pounds and Dollars) constant. Previous researchers have shown that the conversion rate itself may change consumption behavior (e.g., Raghubir et al., 2012). Future researchers may therefore investigate how the interaction between fantasy currencies and different exchange rates influences purchase intentions.

References

Alter, A. L., & Oppenheimer, D. M. (2008). Easy on the mind, easy on the wallet: The roles of familiarity and processing fluency in valuation judgments. *Psychonomic Bulletin and Review, 15*(5), 985–990. https://doi.org/10.3758/PBR.15.5.985

AppsFlyer. (2016). The State of In-App Spending: Golbal & Regional Benchmarks, 2016.

Chang, C. J. (2013). Price or quality? The influence of fluency on the dual role of price. *Marketing Letters, 24*(4), 369–380. https://doi.org/10.1007/s11002-013-9223-8

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. Routledge Academic.

Coop. (2020). Herzlich wilkommen bei Supercard. https://www.supercard.ch/de.html

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. *Journal of Marketing Research, 28*(August), 307–319.

Forbes. (2020). No Cash, No Card, No Problem At Coachella As Cashless Payments Evolve With Mobile Wallets. https://www.forbes.com/sites/brianhernandez1/2016/04/15/cashless-coachella-mobile-payments-apple-android-samsung-pay/?sh=27f53fac661e

Gafeeva, R., Hoelzl, E., & Roschk, H. (2018). What else can your payment card do? Multifunctionality of payment modes can reduce payment transparency. *Marketing Letters, 29*(1). https://doi.org/10.1007/s11002-017-9445-2

Graf, L. K. M., Mayer, S., & Landwehr, J. R. (2018). Measuring Processing Fluency: One versus Five Items. *Journal of Consumer Psychology, 28*(3), 393–411. https://doi.org/10.1002/jcpy.1021

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford Publications. https://doi.org/978-1-60918-230-4

Labroo, A. A., Dhar, R., & Schwarz, N. (2008). Of frog wines and frowning watches: Semantic priming, perceptual fluency, and brand evaluation. *Journal of Consumer Research, 34*(6), 819–831. https://doi.org/10.1086/523290

Mankiw, G. N. (2007). Macroeconomics (6th ed.). Worth Publishers.

Migros. (2020). Cumulus: Punkten und profitieren. https://www.migros.ch/de/cumulus.html

Mishra, H., Mishra, A., & Nayakankuppam, D. (2006). Money: A bias for the whole. *Journal of Consumer Research, 32*(4), 541–549. https://doi.org/10.1086/500484

Motyka, S., Suri, R., Grewal, D., & Kohli, C. (2016). Disfluent vs. fluent price offers: paradoxical role of processing disfluency. *Journal of the Academy of Marketing Science, 44*(5), 627–638. https://doi.org/10.1007/s11747-015-0459-0

Peer, E., Vosgerau, J., & Acquisti, A. (2014). Reputation as a sufficient condition for data quality on Amazon Mechanical Turk. *Behavior Research Methods, 46*(4), 1023–1031. https://doi.org/10.3758/s13428-013-0434-y

Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. *Marketing Science, 17*(1), 4–28. https://doi.org/10.1287/mksc.17.1.4

Princeton University. (2010). About WordNet. https://wordnet.princeton.edu/

Raghubir, P., Morwitz, V. G., & Santana, S. (2012). Europoly Money: How Do Tourists Convert Foreign Currencies to Make Spending Decisions? *Journal of Retailing, 88*(1), 7–19. https://doi.org/10.1016/J.JRETAI.2011.11.001

Raghubir, P., & Srivastava, J. (2008). Monopoly Money: The Effect of Payment Coupling and Form on Spending Behavior. *Journal of Experimental Psychology: Applied, 14*(3), 213–225. https://doi.org/10.1037/1076-898X.14.3.213

Sensor Tower. (2020a). Fortnite Mobile Revenue Hits $1 Billion in Two Years. https://sensortower.com/blog/fortnite-mobile-revenue-1-billion

Sensor Tower. (2020b). Pokémon GO Surpasses $3.6 Billion in Lifetime Revenue as It Celebrates Four-Year Launch Anniversary. https://sensortower.com/blog/pokemon-go-revenue-year-four

Soman, D. (2003). The Effect of Payment Transparency on Consumption: Quasi-Experiments from the Field. *Marketing Letters, 14*(2001), 173–183.

Thomas, M., Desai, K. K., & Seenivasan, S. (2011). How credit card payments increase unhealthy food purchases: Visceral regulation of vices. *Journal of Consumer Research, 38*(1), 126–139. https://doi.org/https://doi.org/10.1086/657331

Tomorrowland. (2020). General Terms and Conditions Tomorrowland 2021. https://www.tomorrowland.com/en/festival/practical/general-terms-conditions

UNHCR. (2020a). Figures at a Glance. https://www.unhcr.org/figures-at-a-glance.html

UNHCR. (2020b). Financials. https://reporting.unhcr.org/financial#_ga=2.33242302.1451492245.1547497798-82531760.1547497798

White, R. (2008). The Mental Accounting of Gift Card versus Cash Gift Funds. *Advances in Consumer Research, 35*, 722. https://login.libproxy.noctrl.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=buh&AN=35063876&site=eds-live

Whittlesea, B. W. A. (1993). Illusions of Familiarity. *Journal of Experimental Psychology:*

*Learning, Memory, and Cognition, 1*9(6), 1235–1253.

Wu, Z., & Palmer, M. (1994). Verbs semantics and lexical selection. *Proceedings of the 32nd Annual Meeting on Association for Computational Linguistics*.

Zellermayer, O. (1996). The Pain of Paying. (Doctoral dissertation). Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA.

Supplemental Material

Study 1: Calculating the Semantic Similarity Measure

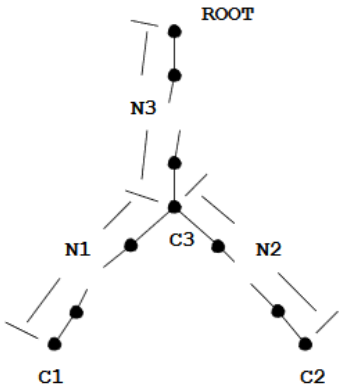


Figure D-5. Hierarchical structure of concepts in WordNet (Wu & Palmer, 1994).

WordNet lexicalizes words and concepts in a hierarchical structure (see Figure D-5 above). Wu and Palmer (1994) proposed the following approach for calculating the similarity between two concepts (C1 and C2) within WordNet's hierarchical structure:

$$ConceptualSimilarity_{WUP}(C1, C2) = \frac{2*N3}{N1+N2+2*N3}$$

To calculate the similarity between C1 and C2 (i.e., *money* and *coin*), we first located the position of the least common superconcepts of C1 and C2: C3 (i.e., *currency*) and the root. After this, we calculated the distances N1 (number of nodes between C1 and C2), N2, and N3, respectively. Lastly, these distance measures were input into the above formula, leading to the following WUP scores for the fantasy currencies used in Study 1:

Table D-1. WUP score calculations

Currency	Formula	WUP
Coin	$\frac{2*8}{1+2+2*8}$	0.842
Gold	$\frac{2*5}{3+4+2*5}$	0.588
Diamond	$\frac{2*4}{4+5+2*4}$	0.471
Gem	$\frac{2*2}{6+4+2*2}$	0.286
Candy	$\frac{2*2}{6+8+2*2}$	0.222

E. ESSAY IV

Scheidegger, G., Linzmajer, M., Rudolph, T., Raghubir, P., and Bischof, S. (submitted). Pay Less, Spend More: Consumers' Mental Accounting for Discounted Gift Cards. *Journal of Marketing Research.*

Scheidegger, G., Linzmajer, M., Rudolph, and Bischof, S. (presented). Pay Less, Spend More: Consumers' Mental Accounting for Discounted Gift Cards. *ACR Conference 2020.*

Pay Less, Spend More:
Consumers' Mental Accounting for Discounted Gift Cards

Co-Authors

Marc Linzmajer[(1)]

Thomas Rudolph[(2)]

Priya Raghubir[(3)]

Severin Bischof[(4)]

Abstract

This article introduces the discounted gift card (DGC) to the field of marketing. Discounted gift cards are relatively new, but their popularity is increasing in price-sensitive industries. In three experiments and one field study, DGCs elicited lower subjective costs and higher spending amounts than other equivalent promotional activities; these results can be explained using a mental accounting framework. Our results show that DGCs are an attractive alternative to regular price discounts that should be considered by companies in a price-sensitive environment. Even small discounts lead to a significant increase in sales in an industry where price is the main driver of choice.

(1) Marc Linzmajer is Director of the Competence Center Shopper Marketing, Inspiration and Pricing & Retail Promoter Program, Institute of Retail Management, University of St.Gallen, Switzerland (marc.linzmajer@unisg.ch).

(2) Thomas Rudolph is Professor of Marketing, Institute of Retail Management, University of St.Gallen, Switzerland (thomas.rudolph@unisg.ch).

(3) Priya Raghubir is Professor of Marketing, Leonard N. Stern School of Business, New York University, USA (raghubir@stern.nyu.edu).

(4) Severin Bischof is Postdoctoral Researcher, Institute of Retail Management, University of St.Gallen, Switzerland (severinfriedrich.bischof@unisg.ch).

1. Introduction

There are two common phenomena affecting pricing in the world today: new methods of payment and new types of promotional offers. There is one mechanism that combines both of these phenomena, namely the discounted gift card (DGC). This paper examines how consumers evaluate DGCs and how this evaluation affects spending decisions. We aim to make a substantive contribution to managerial practice in markets where the use of DGCs is significant and rising.[1]

We hope to shed light on the managerial questions of when a DGC should be issued (that is, how long before its redemption date it must be purchased), the size of the discount to offer, and what proportion of it should be pre-paid – all questions that issuers of DGCs need to make as they design their offers.

Theoretically, we aim to contribute to the understanding of the subjective value of money, the behavioral literature on price promotions, and the process of mental accounting. We first introduce the concept of the DGC and then develop a theoretical framework from which we derive testable hypotheses. These are systematically tested in our empirical package. Three experiments and one field study show that consumers depreciate the face value of a gift card over time, which leads to a subjective underestimation of costs at the time of purchase. The depreciation effect increases with growing face values of the DGCs.

1.1. The Rise of The Discounted Gift Card

Discounted gift cards are company-specific funds in form of a card or code, which can be redeemed for purchase at the card-issuing company only and have been bought for a price below face value. Platforms such as cardpool.com where consumers can sell unwanted gift cards and buy discounted gift cards have been popular for many years. On July 2, 2019, 29,550 discounted gift cards were available on cardpool.com alone (see Table E-2 for the most popular DGCs), with a total value of $1.79M and a combined discount value of $162,659.[2]

Some companies have now also started selling DGCs directly to their customers on special occasions as part of their promotion strategies. In April 2019, for example, Etihad Airways, a national airline based in Abu Dhabi, sold DGCs with a discount of 90% to cus-

[1] Personal conversations with managers of a major European airline and retailers who issued DGCs to maintain cash flow during the COVID-19 pandemic in 2020 indicate the increasing popularity of DGCs.
[2] We collected the information from publicly available data using a web-scraping algorithm.

tomers in Switzerland. In December 2020, one of the world's biggest retailers, Aldi, in cooperation with Apple, offered a 15% discount on 25-, 50-, and 100-euro iTunes and App Store gift cards for German customers.

The DGC is at once a payment mechanism and a price promotion. Below we discuss both aspects of the DGC.

1.2. The Discounted Gift Card as a Price Promotion Mechanism

Price- and deal-sensitive consumers are targeted by a range of different discounts, some easier for the common consumer to comprehend and calculate than others. "3 for the price of 2," "Buy 3 get 1 free," and "Spend $75, get a 10% discount on your cart" are just some examples of price discounts that are trickier to calculate than "$5 off" or "50% off." In 2016, a study in Germany (Statista, 2016) asked 1,001 participants, "Which of the following discounts do you use at least multiple times per year?" The results indicated that 88% used offers in retailer brochures, 81% used loyalty programs, 77% used discount coupons, 68% used coupons for free/additional products, 66% took advantage of loyalty offers, and 55% used gift cards/vouchers.

How these promotional offers affect consumer behavior has attracted the attention of marketing and consumer behavior researchers in recent years (e.g., Chandran & Morwitz, 2006; Cheng & Cryder, 2018; Vana, Lambrecht, & Bertini, 2018), and they have found that these discounts may induce lower cost perceptions and higher expenditures among consumers (e.g., Cheng & Cryder, 2018).

However, to our knowledge, the increasingly popular discount mechanism of the DGC has not been studied. The price discount makes the DGC attractive for personal use. For example, price- and discount-sensitive consumers are likely to be attracted by a $500 gift card for future purchases that is reduced to $400. In fact, cardpool.com advertises, "Welcome to the gift card exchange! Buy discount gift cards. Get up to 35% OFF" and "Turn your gift cards into cash! Have unused gift cards? Sell them to Cardpool & get up to 88% cash back." If consumers view these as good deals, the gift cards could generate cash flow for the company as well as provide a commitment for future sales, a discount for the consumer, and profit for the marketplace.

1.3. Discounted Gift Cards as a New Form of Payment

The DGC is a gift card. However, as many gift cards are not redeemed for their full value (Horne, 2007), leftover gift card balances can constitute an additional source of profit, as can sales over the value of the discounted gift card. Indeed, a gift card's usage rate is, on average, considerably lower than 100% of its face value, with one estimate at 90% of face value being redeemed (Horne, 2007); as such, the DGC can generate additional profits for card issuing companies.

One of many reports forecasting massive growth in the global gift card market (e.g., Comoreanu, 2017; ResearchAndMarkets, 2018; Technavio, 2018) estimates that the gift card sector will grow with a compounded annual growth rate of 10.1% over the next 10 years, reaching an overall market size of $750.31 billion by 2026 (ResearchAndMarkets, 2018). While regular or free gift cards have received a great deal of attention from researchers (e.g., Khouja, Pan, Ratchford, & Zhou, 2011; Raghubir & Srivastava, 2008; Reinholtz, Bartels, & Parker, 2015; Valentin & Allred, 2012; White, 2006; Yao & Chen, 2014), little is known about DGCs and their influence on consumers' perception and spending. Up to this point, gift cards have been considered something people receive as a gift, bonus, or as part of a promotion. However, a DGC can be attractive for self-purchase as well because its selling price lies below its face value. Thus, the product becomes relevant for an even larger group of customers and is not limited to gift-givers and receivers.

1.4. Discounted Gift Cards as Both a Promotion and Payment Mechanism

Discounted gift cards are both a form of price promotion and payment. A relevant question for issuers is how the combination of the promotional aspect of a DGC and its lower transparency affect consumers' purchase decisions. Because its selling price lies below its face value, the main consumer motivation for buying a DGC arguably comes from the idea that it is a good deal, although consumers may ultimately spend more by buying such cards, buying extra products over and above the face value of the card they have, or not using the cards for their full face value. In all cases, the card issuer profits. The DGC's price discount incentivizes consumers to switch from paying cash at the time of purchase to a less transparent form of payment: gift cards for planned future purchases. Notably, there is already evidence that using less transparent payment mechanisms leads to overspending via subjective underestimation of costs (e.g., Soman, 2003).

1.5. The Mental Accounting of Discounted Gift Cards

Building upon these findings, we aim to examine how consumers mentally account for DGCs and whether their mental accounting influences the subjective costs of the purchase and spending. In addition, we aim to supplement the mental accounting literature by describing how consumers account for (partially) prepaid consumption and past discounts at the time of purchase. Previous research has already identified several factors that may influence consumers' consumption behavior, including the time difference between payment and consumption (Gourville & Soman, 1998; Shafir & Thaler, 2006), also referred to as payment coupling (Cheng & Cryder, 2018; Raghubir & Srivastava, 2008); the form of payment (Chatterjee & Rose, 2012; Khouja et al., 2011; Raghubir & Srivastava, 2008; Soman, 2001, 2003; White, 2008); and the categorization of payments (e.g., Prelec & Loewenstein, 1998; Thaler et al., 2000). In sum, extant research has already addressed how different *promotion types* (e.g. gift cards, cashback, absolute vs. relative discounts, etc.) and *payment mechanisms* (e.g. credit cards, checks, cash, etc.) influence consumers' purchase decisions.

Discounted gift cards fall into both groups as a promotion type as well as a payment mechanism. Again, the card discount incentivizes consumers to switch from more transparent cash (or credit card) payments to a less transparent payment mechanism – one similar to what Soman (2003) classified as "stored-value cards." In addition, when the cost of the product exceeds the face value of a DGC, consumers may mix several payment mechanisms at the time of the purchase. Therefore, only part of the purchase has already been prepaid.

The combination of the discount and payment mechanism as well as partial prepayment makes DGCs an interesting research subject from a mental accounting perspective. As no one has looked at the interplay of these factors before, we address this research gap by systematically disentangling and analyzing consumers' processing of the DGC's purchase process. In this way, we seek to understand how DGCs face value, prepayment, and the interaction between those two affect consumers' subjective costs at the time of product purchase. Next, we present the theoretical background.

2. Theoretical Background

2.1. Mental Accounting for Price Discounts and Gift Cards

Mental accounting has been described as the consumers' process of keeping track of their own money-related spending. This process involves financial decision-making, its subsequent evaluation, and categorizing financial expenditures into different mental accounts (Shafir & Thaler, 2006; Thaler, 1985; Thaler & Benartzi, 2004; Thaler, Kahneman, & Tversky, 2000). Broadly speaking, consumers categorize their assets into two accounts: (1) current income and (2) current wealth (Shefrin & Thaler, 1988). Whereas the money in the current wealth account is handled conscientiously, consumers may be tempted to spend money assigned to the current income account (Shefrin & Thaler, 1988). Windfall gains, such as unexpected price discounts, are usually assigned to the current income account (Arkes et al., 1994; Heilman et al., 2003; Milkman & Beshears, 2009; Vana et al., 2018). On the one hand, consumers initially save money through the discount. On the other, they are more likely to buy products they usually would not buy (Milkman & Beshears, 2009) and increase the size of the purchase (Heilman et al., 2003; Milkman & Beshears, 2009; Vana et al., 2018) when accounting for the discounts as "current income."

Consumers use a similar approach when accounting for gift cards. They perceive gift cards differently than cash money (Raghubir & Srivastava, 2008; Valentin & Allred, 2012; White, 2008; Yao & Chen, 2014) because of its alternative payment form and low payment transparency (Soman, 2003). Due to their limited redemption possibilities, consumers perceive the monetary value of a gift card as a shopping budget (Reinholtz et al., 2015; White, 2006) and as less attractive than their cash equivalent (Offenberg, 2007).

Gifted cash recipients decide whether to buy something or not. In contrast, gift card recipients usually decide what they want to buy, how, and when they want to buy it (Reinholtz et al., 2015; Yao & Chen, 2014). In doing so, gift card users tend to overspend the card's face value (Thomas & Dillenbeck, 2004; White, 2006, 2008). One reason for this overspending might be that they want to minimize unspent funds, which are regarded as a monetary loss (White, 2006, 2008). In addition, redeeming a gift card rather than paying cash makes consuming personal luxuries less guilt-inducing (Valentin & Allred, 2012), which might increase consumption.

In sum, we hypothesize that it is the combination of both the discount – accounted for as current income – and the low payment transparency of a gift card that reduces consumers' subjective costs at the time of the purchase. Although the DGC resembles other price promotions designed to incentivize immediate purchases, such as regular price discounts (e.g. "$100

off"), DGC is distinct from these promotions. Receiving a DGC is conditional on the initial purchase of the gift card and its redemption through a future purchase. Therefore, DGCs represent partially prepaid consumption as well as a pre-received promotion compared with other similar price promotions. To test whether DGCs reduce subjective costs of purchases and associated spending, we propose the following hypothesis:

H1: Consumers who receive DGCs (a) report lower subjective costs and (b) spend more than consumers who receive a financially equivalent price discount.

2.2. Temporal Separation in Payment Mechanisms

Temporally separating payment and consumption may lead to counterintuitive financial decisions (Arkes & Blumer, 1985; Gourville & Soman, 1998; Prelec & Loewenstein, 1998; Shafir & Thaler, 2006; Thaler, 1980). Sunk costs (Arkes & Blumer, 1985) are probably the most prominent example of this effect. When consumption and payment are temporally separated, the impact of sunk costs decreases (Gourville & Soman, 1998). Hence, the greater the time difference, the less the consumption decision is influenced by the upstream costs.

Gourville and Soman (1998) referred to this phenomenon as payment depreciation. They found that people are less likely to attend a basketball game during a snowstorm or to go to the gym the more that time passes between payment and the decision to attend. Conversely, when no payment has been made, there are no costs to depreciate. This means that when basketball tickets are received for free, the likelihood of attending does not change with increasing time difference (Gourville & Soman, 1998). Prelec and Loewenstein (1998) explained the tendency of increased spending when using a credit card (e.g., Feinberg, 1986; Prelec & Simester, 2001; Soman, 2001) with the temporal separation between the purchase of the product and payment of the credit card bill. In certain cases, the consumption would even feel completely free if it had been paid for in the past (Prelec & Loewenstein, 1998; Shafir & Thaler, 2006).

After conducting a series of interviews, Soman (2003) ranked several payment mechanisms based on what he termed "payment transparency." With payment transparency, Soman (2003) referred to the similarity between the respective payment mechanism and cash payments, which serve as a baseline for the ranking. The lower the payment transparency of a payment mechanism, the harder it is for consumers to keep track of their expenses and the higher their tendency of spending more money than consumers paying cash (Soman, 2003). Table E-1 summarizes his findings and shows that cash has the highest transparency, while discounted gift cards have among the lowest transparency. When payments are made after purchase, transparency decreases with increasing time difference (Soman, 2003). Examples

for payment mechanisms involving prepayment are stored-value cards, such as prepaid laundry cards, students' photocopy cards (Soman, 2003), or DGCs (this article).

Table E-1. Transparency levels of different payment mechanisms

Payment mechanism	**Relative timing of money outflow and purchase**	**Transparency**
Cash	Concurrent	High
Check	Payment after purchase	Medium
Credit card	Payment significantly after purchase	Low
Debit card	Concurrent	Low
Stored-value cards, Discounted gift cards	Payment before purchase	Very low
Autopay (direct debit from bank account)	Concurrent	Very low

Consumers experience an unpleasant feeling known as "pain of paying" whenever they spend money (Knutson et al., 2007; Prelec & Loewenstein, 1998; Zellermayer, 1996). The concept of pain of paying is closely linked to consumers' subjective costs. In fact, pain of paying is not caused by the cost of the purchase itself but rather by consumers' subjective perceptions of a certain cost (Cheng & Cryder, 2018; Gourville & Soman, 1998; Knutson et al., 2007; Morewedge et al., 2008; Soman, 2001). According to Prelec and Loewenstein (1998) as well as Soman (2003), pain of paying, which decreases the pleasure derived from consumption, can be reduced by lowering the transparency of a payment mechanism. Combined with the fact that transparency decreases with increasing time difference (Soman, 2003), we hypothesize the following:

H2: The longer the time span between the DGC purchase and its redemption, the lower the subjective costs for consumers.

We visualize this hypothesized relationship in Figure E-1.

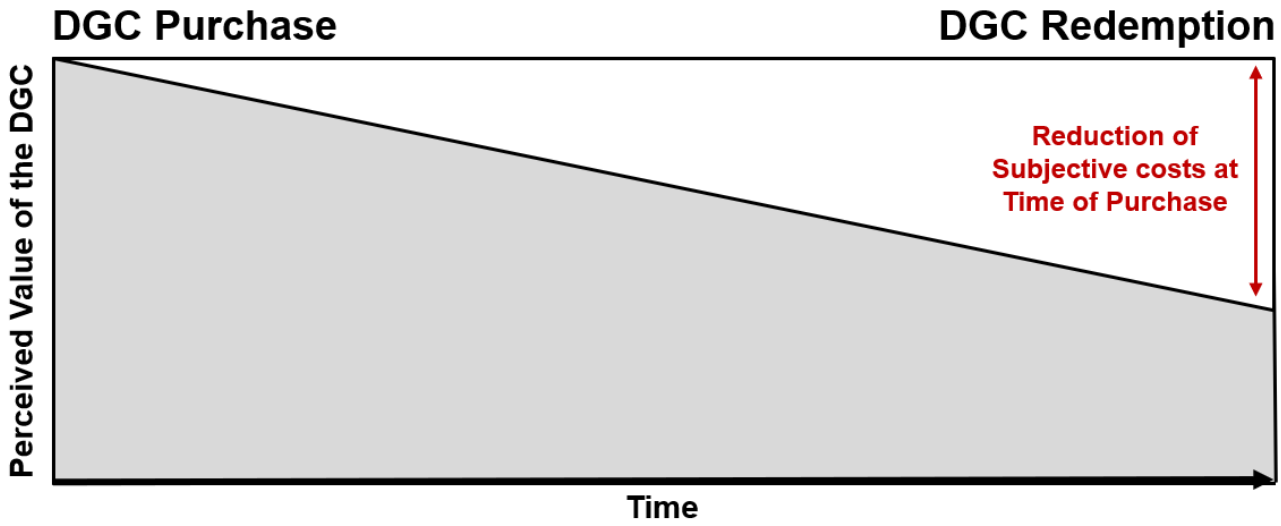


Figure E-1. Hypothesized relationship between time gap (DGC purchase and DGC redemption) and reduction of subjective costs.

Finally, Gourville and Soman (1998) argued that payments depreciate monotonically and continuously in relation to the payment amount. They expressed payment depreciation with the following exponential decay function: $V_t\ (x) = V_0\ (x) * e^{-dt}$. V_t (x) stands for the perceived value of a payment *x* at time *t*, and *d* represents the rate of depreciation. When we apply the same decay function to different gift card prepayments (i.e., face values) as in Figure E-2, we can observe that nominally the depreciation (expressed by the negative slopes) increases with increasing face values.

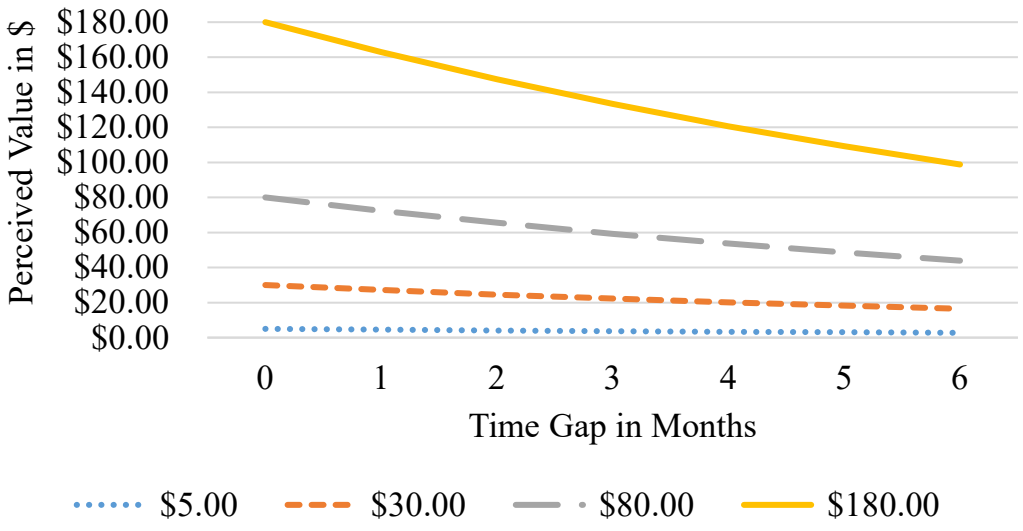


Figure E-2. Exemplary payment depreciation for different DGC face values assuming Gourville and Soman's (1998) exponential decay function with d = .1 and t between zero and six months.

We therefore hypothesize the following:

H3: The face value of a DGC negatively influences consumers' subjective costs if nominal discount and the time gap between DGC purchase and product purchase are held constant.

The empirical package includes the following studies: In Study 1, we compare different promotion types to DGCs to analyze how each of these influence subjective costs (H1 and H2). Study 2 tests how consumers depreciate costs over time depending on prepayment (H2). Study 3 tests the influence of DGCs face values on payment depreciation (H3). Study 4 concludes by providing external validity using field data.

3. Study 1: Discounted Gift Cards vs. Regular Gift Cards and Regular Price Discounts

Study 1's goal was to test H1, or the effect of DGCs versus equivalent price promotions and regular gift cards on cost perceptions (H1), especially when there is a larger time gap (H2).

3.1. Method

We used a 3 x 2 between-subjects design, recruiting six hundred ninety-seven US-based participants (female = 46.2%, median age = 34 years) with a task approval rate of at least 95% (see e.g., Peer et al., 2014) through Amazon MTurk (AMT). Despite some discussion about the validity of findings from MTurk (Boden, Maier, and Wilken 2020), previous research notes the diverse demographics of the sample (Berinsky et al., 2012) and finds reliability and validity at least on par with other potential samples (such as students; Hauser and Schwarz, 2016). At the beginning of the study, we asked all participants to read the content of an e-mail they had received. Depending on the experimental condition they had been randomly assigned to, they either read (1 – DGC condition) *BIRTHDAY DEAL BY SPRUCE AIRLINES! Get a $400 Flight Voucher from Spruce Airlines for $300 only. You decide to buy one voucher*; (2 – regular gift card condition) *A FRIEND WISHES YOU A HAPPY BIRTHDAY! Please find a $100 Flight Voucher from Spruce Airlines attached*; or (3 – discount condition) *FUTURE DEALS BY SPRUCE AIRLINES! Look out for Spruce Airline deals in the future. It might be worth it.* Then, either one day later or six months later, depending on the nested condition, all participants had to imagine themselves living in New York and planning their spring holidays in Rome, Italy. As they were looking for flights, they found a suitable offer with Spruce Airlines for $500. For participants in conditions 1 and 2, we reminded them of the voucher they had previously (one day or six months ago) received or acquired. In

condition 3, the $500 flight was discounted by $100. After booking the fictitious flight, we measured participants' subjective costs[3] (Cheng & Cryder, 2018; Shafir & Thaler, 2006) by asking them *"How much does it feel like you are spending on the flight?"* Lastly, we asked all participants how much they would have been willing to pay (maximum) for the flight in an open-ended format.

3.2. Results

A 3 (promotion type) x 2 (time) ANOVA on subjective costs yielded a significant main effect of promotion type ($F(1, 691) = 40.77$, $p < .001$, $\eta^2 = .11$, $R_a^2 = 11.1\%$), with subjective costs in the DGC condition (M = $332.77, SD = $146.98) being lower than in the regular gift card condition (M = $404.53, SD = $87.60) or in the price discount condition (M = $422.41, SD = $117.86). While the main effect of time was not significant ($F < 1$), the interaction was significant ($F(1, 691) = 3.36$, $p = .04$, $\eta^2 = .010$). Thus, H1a was supported.

Planned contrast analyses revealed a significant difference in subjective costs between the 1 day later (M = $350.64, SD = $140.57) and the 6 months later condition (M = $317.72, SD = $149.67) when a DGC was offered ($F(1, 691) = 5.095$, $p = .02$, $\eta^2 = .007$), such that subjective cost perceptions decreased with a longer time span. In contrast, there was no difference in subjective costs between the one day later (M = $398.33, SD = $95.25) and the six months later conditions (M = $411.16, SD = $78.474) when a regular gift card was offered ($F < 1$) as well as when a price discount was offered ($M_{1\text{ day later}} = \$415.18$, $SD_{1\text{ day later}} = \$86.18$; $M_{6\text{ months later}} = \$429.22$, $SD_{6\text{ months later}} = \$93.45$; $F < 1$). Thus, H2 was supported.

3.3. Discussion

Objectively, participants across all conditions – independent of the discount type or time difference between the purchase and the e-mail – received a $100 price reduction on their $500 flight to Rome. Nonetheless, as visualized in Figure E-3, the time and discount conditions significantly influenced consumers' cost perceptions. Participants who received DGCs in a hypothetical purchase scenario showed substantially lower subjective cost perceptions compared with a financially equivalent discount. This effect appeared one day after the purchase of the DGC, and it was amplified over the course of six months. The distributions in Figure E-3 demonstrate that the values of regular gift cards and regular discounts behave

[3] Subjective costs have been established as a suitable dependent variable in the context of gift cards and mental accounting (e.g., Cheng & Cryder, 2018). Throughout all studies, we excluded subjective cost values above the 75% quartile + 3*IQR and below the 25% quartile – 3*IQR. The results do not differ substantially when those values are removed compared to winsorizing them.

very similarly. In contrast, the distribution of DGCs over the time scenarios differs significantly from the other discount types. These results support H1a and H2 as they indicate that DGCs have different effects on consumers' cost perceptions than regular discounts and gift cards. Users of DGCs report lower subjective costs than users of regular gift cards and consumers receiving regular price discounts of equivalent values, supporting H1a. In addition, a decrease is shown in subjective costs over time for consumers using DGCs in comparison to the other two groups, supporting H2.

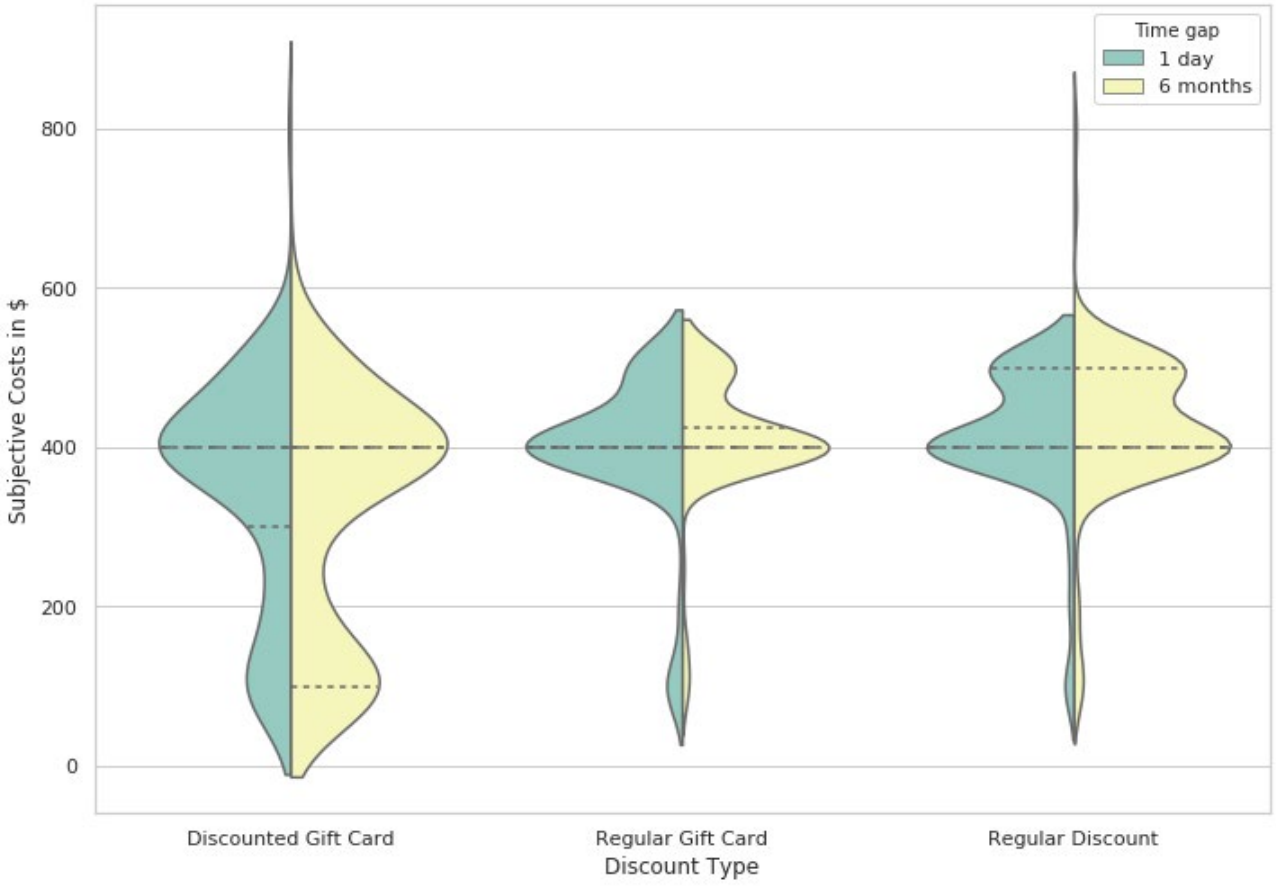


Figure E-3. Distribution of values across all scenarios grouped by discount type. Dashed lines in the distribution correspond to the quartiles. In most distributions, some quartiles overlap. For example, in both DGC scenarios, the median and 75% quartile overlap. Please note that the values in the graph extend past the largest and smallest values in the dataset; this is due to the Gaussian kernel density estimation (KDE) used for plotting this graph. All values fell between $100 and $800. These so-called "violin plots" are similar to box plots but allow a more comprehensive view of the data distribution as they include additional information about the probability density for different values of the data (see e.g., Thrun et al., 2020).

4. Study 2: Payment Depreciation in Discounted Gift Card-Usage

In Study 2, we aimed to shed light on the process of payment depreciation by comparing two forms of DGCs: one with substantial prepayment and the other with almost no prepayment. The decision on the prepaid amount is also a managerially relevant. In line with the theoretical concepts of mental accounting, we argue that only prepayments can depreciate. In contrast, we expect that gift cards that have been received for free will not be subject to payment depreciation. In other words, when using DGCs at the time of purchase, subjective costs will decrease with the increasing time gap between DGC purchase and purchase of the product. Conversely, users of a gift card that was given to them for free will show no differences in subjective costs over time.

4.1. Method

In a 2 x 2 between-subjects online experiment with four hundred sixty-three US-based participants (54% female, median age = 35 years, task approval rate ≥ 95%) from AMT, we tested whether DGCs are subject to payment depreciation. We told half of the participants that they would acquire a $500 gift card online from Best Buy for only $400 ($100 discount). The other half served as a control condition and received the same gift card for $1 only ($499 discount). We included this high discount as a control condition to show that only payments are subject to depreciation; Gourville and Soman (1998) included a similar control by adding a free ticket condition to their experiment. We sought to be as close to the regular DGC scenario as possible by letting consumers purchase the DGC for a symbolic dollar rather than getting it for free.

For the second part of the study, we told participants that they would redeem the DGC for an $800 laptop either one day or six months later. Other than the time difference between the purchase of the DGC and the purchase of the laptop, the purchase scenarios were identical. Lastly, we measured participants' subjective costs in an open-ended format (see Study 1; Cheng & Cryder, 2018; Shafir & Thaler, 2006).

4.2. Results

A 2 (discount type) x 2 (time) ANOVA on subjective costs yielded a significant main effect of discount type ($F(1, 459) = 127.909$, $p < .001$, $\eta^2 = .218$, $R_a^2 = 22.00\%$), with subjective costs in the $100 discount condition (M = $549.49, SD = $213.39) unsurprisingly higher than in the $499 discount condition (M = $345.62, SD = $174.28). While the main effect of

time was not significant ($F(1, 459) = 1.242$, $p = .25$), discount type by time interaction was significant ($F(1, 459) = 4.23$, $p = .04$, $\eta^2 = .009$).

Planned contrast analyses revealed higher subjective costs in the one day later (M = \$578.07, SD = \$208.30) versus the six months later condition (M = \$520.91, SD = \$215.49) when a DGC was offered with a \$100 discount ($F(1, 459) = 4.99$, $p = .03$, $\eta^2 = .011$). In contrast, there was no difference in subjective costs when a \$499 discount was offered between the one day later (M = \$337.095, SD = \$156.01) and the six months later condition (M = \$354.07, SD = \$190.97; $F < 1$). These findings support the idea that DGCs operate via a payment depreciation process.

In line with Hypothesis 1a, in both time conditions, DGCs significantly lowered subjective costs of participants below the objective costs of \$700 ($t(114) = -6.28$ and -8.91, $p < .001$ for one day versus six months, respectively). In both control non-DGC conditions, mean subjective costs were significantly higher than objective costs of \$301 ($t(115) = 2.49$ and $t(116) = 3.01$, $p = .01$ and .003 for one day versus six months, respectively).

Next, we conducted a moderation analysis using Hayes' (2017) PROCESS macro with 5,000 bootstrap samples across both conditions. Time difference (0 = one day vs. 1 = six months) and scenario (0 = control condition vs. 1 = regular DGC condition) were our independent variables and subjective costs our dependent variables. The overall model ($F(3, 459) = 44.43$, $p < .001$) as well as the scenario ($b = 203.83$, $p < .001$) and the interaction term ($b = -74.13$, $p = .04$) were statistically significant. We found a significant conditional effect of time difference on subjective costs. When a DGC was used for the purchase, time difference had a significant negative effect on subjective costs (95% CI = [-107.42, -6.89], $b = -57.16$, $t = -2.23$, $p = .03$). For regular gift card users, there was no significant conditional effect of time difference on subjective costs (95% CI = [-32.97, 66.92], $b = 16.97$, $t = .67$, $p = .50$).

4.3. Discussion

The results summarized in Figure E-4 present two effects of a DGC. Firstly, subjective costs are significantly reduced by means of the gift card already one day after the purchase of the DGC, further confirming the results of Study 1. Secondly, we show how subjective costs depreciate when the DGC involved substantial prepayment. On the other hand, when the DGC was received almost for free (control condition), there was no cost to depreciate and therefore no depreciation. These results are in line with literature on payment depreciation of sunk costs (e.g., Gourville & Soman, 1998) and support Hypotheses 1a and 2.

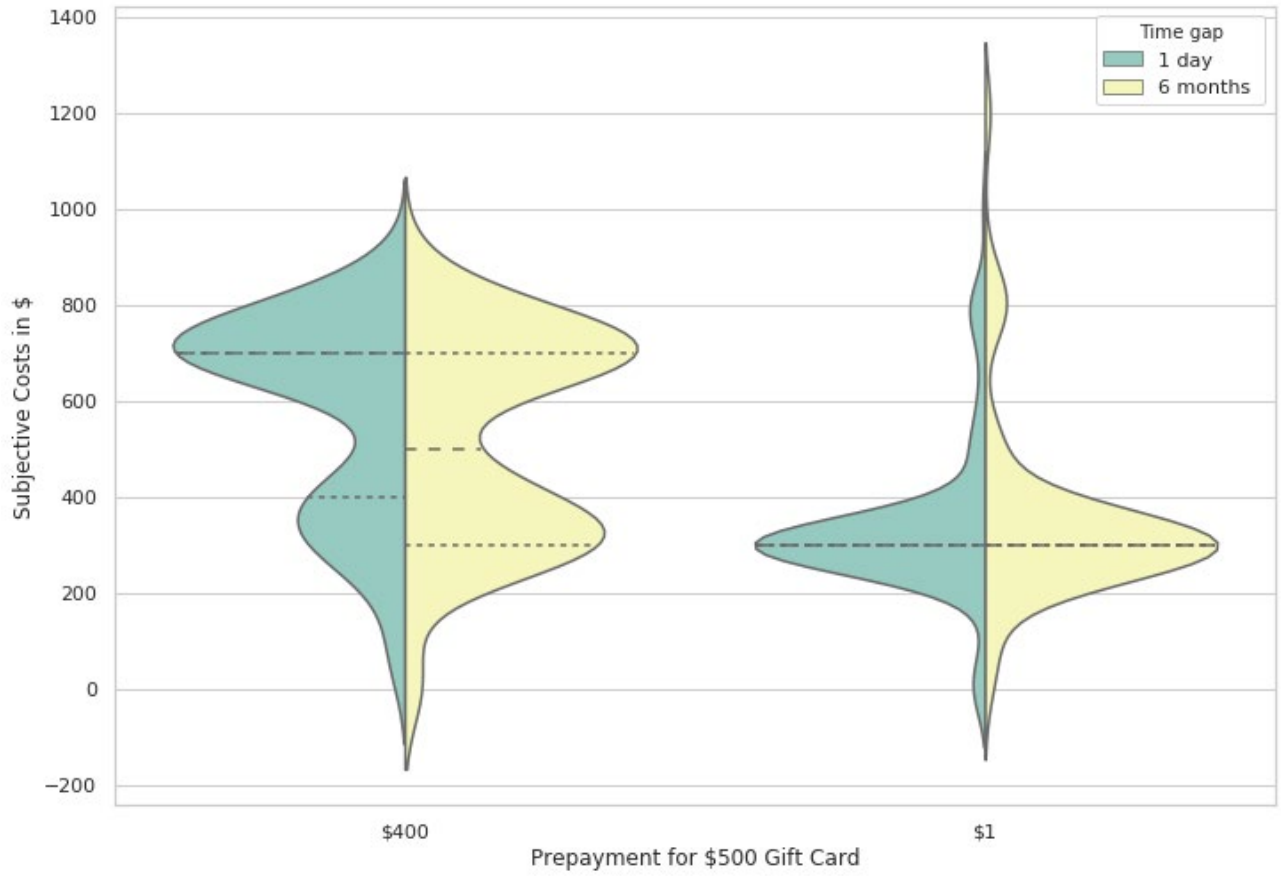


Figure E-4. Distribution of values across all scenarios grouped by gift card type. $1 = control condition and $400 = DGC condition. Dashed lines in the distribution correspond to the quartiles. In the two curves in the control condition, all quartiles overlap at $300 (objective costs). For the DGC condition, the median and 75% quartile overlap in the "one day later" scenario. Please note that the values in the graph extend past the largest and smallest values in the dataset; this is due to the Gaussian KDE used for plotting this graph. All values fell between $0 and $1,200.

5. Study 3: The Influence of Discounted Gift Card Face Values

In Study 3, we investigated payment depreciation among DGCs of different face values while holding the absolute discount constant to test H3. We expected that the higher the face value of a DGC, the stronger the effect of temporal separation on subjective costs (i.e., payment depreciation).

5.1. Method

We recruited five hundred eighty-four US-based participants (median age = 34 years, female = 48.1%, task approval rate ≥ 95%) through AMT. In four between-subjects experimental conditions, we manipulated different DGC face values while holding the nominal discounts constant at $20. To ensure external validity, the DGCs' face values for the different conditions were chosen based on the data we collected from the popular card exchange platform cardpool.com. Table E-2 shows the 10 most popular face values by the number of cards offered on the platform (total number of cards = 29,550). The face values chosen ($25, $50, $100, and $200) cover 69% of all cards offered on the platform.

Table E-2. Ten most popular gift card face values on cardpool.com.

Face Value in $	***Number of Offers***	***% of Total***
25	**8,180**	**28%**
50	**8,106**	**27%**
100	**3,633**	**12%**
20	1,366	5%
75	1,079	4%
40	1,046	4%
15	884	3%
30	753	3%
200	**558**	**2%**
45	504	2%

After the purchase of the DGC ($25 for $5 vs. $50 for $30 vs. $100 for $80 vs. $200 for $180), all participants were told that they would go to a Best Buy store six months later. At the store, all participants were informed that they bought a $300 laptop using their DGC. We then measured their subjective costs by asking *"How much does it feel like you are spending on the laptop (in USD)?"* The answers were given in USD and in open-ended format.

We included a manipulation check in which we asked all participants how much of the purchase price of the laptop had already been prepaid by the purchase of the DGC on a scale of 1 to 7 (1 = only a fraction, 7 = almost the whole amount).

5.2. Results

The manipulations for the DGCs' face values were successful. The higher the face value of the DGC, the higher the participants' perceived amount of prepayment ($F(3, 580) = 64.65$, $R_a^2 = 24.70\%$, $p < .001$, $\eta^2 = .251$).

We conducted an ANOVA with DGC face value as the independent variable and subjective costs (in $) as the dependent variable. Overall, the subjective costs were significantly lower than the objective costs of $280 ($t(583) = -10.33$, $p < .001$). Face value had a significant effect on consumers' subjective costs ($F(3, 580) = 11.64$, $R^2 = 5.7\%$, $p < .001$, $\eta^2 = .057$). Planned contrast analyses revealed that the subjective costs decreased with increasing DGC face value (Figure E-5). There was no statistical difference between subjective costs for $25 DGC users (M = $265.85, SD = $81.45) and $50 DGC users (M = $259.41, SD = $82.09, $F < 1$). However, participants in the $100 DGC condition (M = $234.29, SD = $77.33) indicated significantly lower subjective costs than those in the $50 ($F(1, 580) = 6.35$, $p = .01$, $\eta^2 = .011$) or $25 conditions ($F(1, 580) = 10.21$, $p < .001$, $\eta^2 = .017$). Correspondingly, participants in the $200 condition displayed lower subjective costs (M = $214.07, SD = $96.17) than those in the $25 ($F(1, 580) = 27.57$, $p < .001$, $\eta^2 = .045$), $50 ($F(1, 580) = 20.76$, $p < .001$, $\eta^2 = .035$) or $100 DGC conditions ($F(1, 580) = 4.23$, $p = .04$, $\eta^2 = .007$).

5.3. Discussion

The results of Study 3 support Hypothesis 3 that the face value of a DGC negatively influences consumers' subjective costs. In line with the exponential decay function suggested by Gourville and Soman (1998), our results imply that a DGC's prepayment depreciates in relation to its face value. In addition, the results show that DGCs succeed in reducing consumers' cost perceptions even without giving away too much relative discount. The next study examines the external validity of our experimental results.

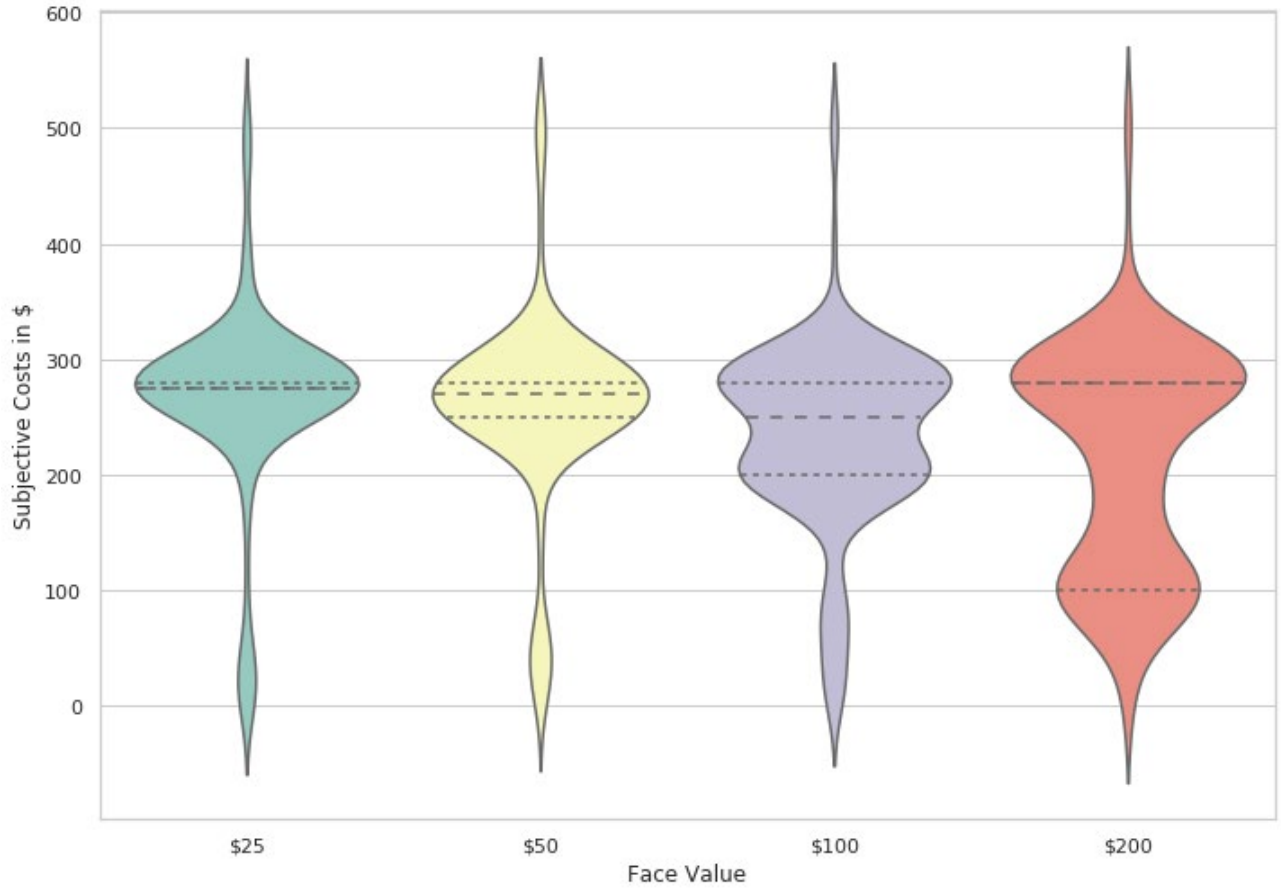


Figure E-5. Distribution of values across all scenarios grouped by DGC face values. Dashed lines in the distribution correspond to the quartiles. The distribution is "stretched" to the bottom of the subjective costs measure with increasing face values. Please note that the values in the graph extend past the largest and smallest values in the dataset; this is due to the Gaussian KDE used for plotting this graph. All values fell between $1 and $500.

6. Study 4: External Evidence of Payment Depreciation in Discounted Gift Cards

To examine whether DGCs affect consumer purchase decisions, we used a unique research opportunity with an international airline to examine the external validity of the findings of Studies 1 to 3.

6.1. Method

On Cyber Monday 2017, the airline issued a limited number of DGCs, which was communicated to their customers through an e-mail newsletter. According to the project manager at the airline, most sold out within only a few hours – an indication of the high attractiveness of DGCs. At the request of our partner company, we anonymized the currency as well as the ticket prices. We multiplied all prices by the same factor. This transformation does not affect our results. The two DGCs had a face value of 30 and 90 monetary units (MU) with an absolute discount of 6 and 15 MU, respectively. About nine months later, we received booking data of DGC and regular gift card bookings since the issuing of the DGCs. The booking data was limited to long-haul flights in economy class. To ensure comparability, we only considered regular gift cards of the same face value as the DGC (30 and 90 MU) in our analyses.

6.2. Results

In order to validate payment depreciation of DGCs in the field, we tested whether the time difference between the generation date of the gift card had a significant positive effect on the booking price. The partner company's gift card system only tracked the internal date when the gift cards were generated by their system. Therefore, the generation date does not necessarily correspond to the purchase date of the gift card. Nevertheless, the generation date is still a suitable indication of the time that passed between the purchase of the gift card and purchase of the flight, allowing for a test of H2, the payment depreciation hypothesis.

We conducted a moderation analysis using Hayes' (2017) PROCESS macro with 5,000 mean-centered bootstrap samples and ticket prices as the dependent variable, time difference (in days) as the independent variable, and gift card type (0 = regular vs. 1 = DGC) as the moderator. While the overall model was significant ($F(3, 208) = 3.64$, $R^2 = 5\%$, $p = .01$), neither gift card type ($b = 23.34$, $p = .48$) nor time difference ($b = .047$, $p = .18$) had a significant effect on ticket prices. However, we found a significant interaction effect ($b = .368$, $p = .03$) between gift card type and time difference. A simple slope analysis revealed that a significant conditional effect of time difference on booking price only exists when consumers

were using a DGC (95% CI = [.017, .683], b = .350, t = 2.07, p = .04). For regular gift card users, there was no significant conditional effect of time difference on booking prices (95% CI = [-.060, .025], b = -.017, t = -.08, p = .42). The moderation effect is visualized in Figure E-6.

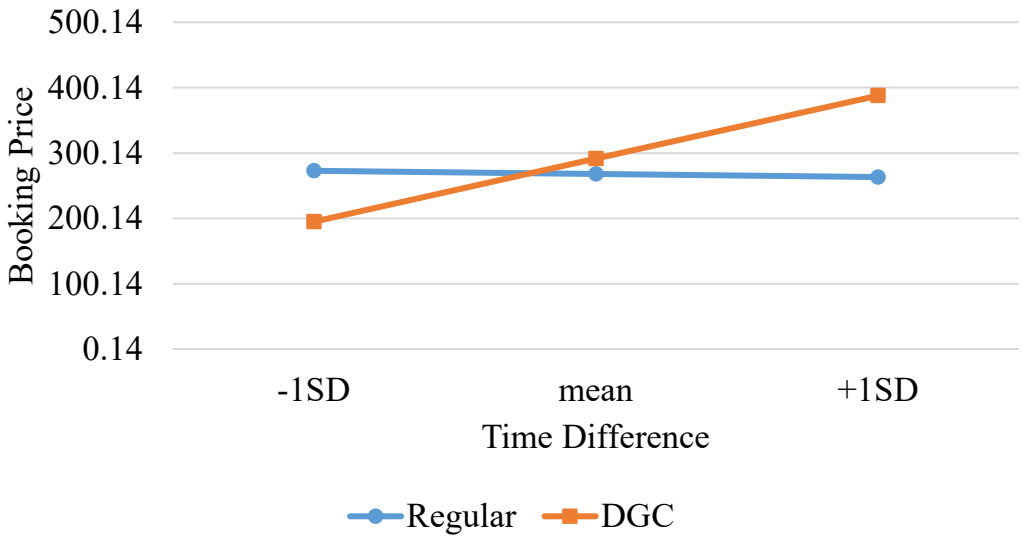


Figure E-6. Relationship between time difference and booking price moderated by gift card type (regular vs. DGC) at low (mean - 1SD) mean and high (mean + 1SD) values of time difference.

The time differences of non-DGC bookings showed considerably more variation than those of DGC bookings. Thus, to check the robustness of our results, we conducted an ANOVA for bookings falling between zero and 260 days after the gift card was generated. This observation period corresponds to that of bookings made using DGCs. Again, time difference (b = -.043, p = .69) had no significant effect on booking prices ($F(1, 88)$ = .162, R^2 = .20%).

6.3. Discussion

Due to the high competitiveness of the airline business and the large number of flight options from competing airlines a consumer can choose from, we interpreted the paid booking prices as an indication of the amount a consumer was willing to pay. The results of our analysis of the field data demonstrate that passengers booking their flight with DGCs spend more compared to a regular gift card the longer they own the DGC. These results from the field support Hypotheses 1b and 2.

7. General Discussion

This paper examined consumers' subjective costs in purchases with DGCs. It supported that subjective costs decrease when consumers receive DGCs, and this decline is greater when more time elapses between the acquisition of the DGC and the purchase decision. In addition, higher face values of DGCs amplify the effect on subjective costs.

Four studies explore the DGC effects compared to well-researched promotional activities: DGC users report lower subjective costs than users of regular gift cards and consumers receiving a regular price discount of an equivalent value. In Studies 1, 2, and 3, we saw that temporally separating the purchase of a DGC and its redemption can further lower consumers' subjective costs of a subsequent product purchase. In addition, the results from Study 1 and 2 suggest that this effect only appears in DGCs and not in regular gift cards or regular discounts. Study 4 uses field data to demonstrate that passengers booking their flight with DGCs spend more the longer they own the DGC. These results connect to previous findings in the literature that reduced subjective costs increase willingness to pay (e.g., Cheng & Cryder, 2018). The results of Study 3 extend the DGC effects with regard to different face values: the higher the face value of a DGC, the lower consumers' subjective costs.

7.1. Theoretical contributions

Discounted gift cards represent a conceptually new phenomenon subject to malleable mental accounting. With this investigation of DGCs' effects, we introduce a new payment mechanism and promotion type to the academic literature. This article contributes to mental accounting literature by showing payment depreciation not only in the context of sunk costs but also in regular product purchases based on partial rather than complete prepayment. Previous mental accounting research has demonstrated that consumers flexibly assign money to different mental accounts and depreciate money in those accounts over time to maximize their transaction utility (Gourville & Soman, 1998; Thaler, 1985; Shafir & Thaler, 2006). We can observe this behavior in our findings as well. Participants do not show the same level of subjective costs in all DGC conditions. Rather, the levels of subjective costs are dependent on the time gap between purchase and redemption of the DGC as well as prepayment level and face value.

Time drives the effect of DGCs on subjective costs and spending amounts. Existing research shows that people procrastinate in redeeming gift cards with long deadlines more than those with short deadlines (Shu & Gneezy, 2010). The results of these studies focus on lower redemption rates but do not consider cost perceptions and corresponding procrastination in purchase decisions. Research on consumer impulsivity would predict that consumers

want an immediate reward after receiving a DGC instead of procrastinating in making a subsequent purchase. We contribute to this literature stream by showing that the immediate reward-seeking tendency of consumers might be beneficial when possessing a DGC. A longer timespan does not lead to a more informed decision – in contrast, subjective costs decrease even further as time passes.

7.2. Implications and Future Directions

The managerial implications of our results are straightforward. When consumers use DGCs, their subjective costs decrease, which entices them to spend more. This makes DGCs an attractive alternative to regular price discounts that should be considered by companies in a price-sensitive environment. DGCs led to the highest decrease in subjective costs compared to regular price discounts and regular gift cards of the same monetary value (Study 1). We highlighted that even shallow absolute discounts can lead to a significant increase in booking prices in the competitive airline industry (Study 3). What is even more interesting, in Study 3, we observed the largest effects on subjective costs when only a 10% discount was given – a discount level that is usually considered very low (e.g., Hardesty & Bearden, 2003; Kalwani & Yim, 1992). Participants in the highest face value condition in Study 3 ($180 for $200 gift card) reported subjective costs ($214) that were over 20% lower than the objective costs ($280). Businesses operating with thin margins may benefit substantially from achieving a perceived discount of over 20% by offering an actual discount of 7% ($280 instead of $300).

In addition, gift card users only redeem part of a gift cards' face value, on average. Thus, the unredeemed funds can partially or even fully compensate companies for the gift card's discount. Another advantage of DGCs over regular price discounts is that discounts in the context of DGCs are offered on the payment mechanism (i.e., gift card) rather than on a single product; this leaves reference prices of products unaffected by the discount. Previous research has shown that offering regular price discounts can have negative effects for businesses as they shape the customers' reference prices and, thus, make them more price-sensitive (Dekimpe, Hanssens, & Silva-Risso, 1998; Kalwani & Yim, 1992; Kaul & Wittink, 1995; Mela, Gupta, & Lehmann, 1997; Pauwels, Hanssens, & Siddarth, 2002).

We investigated payment depreciation of DGCs over a relatively short period of time, six months in experimental studies and about 9 months in the field study. Considering that gift cards usually only expire after several years, future researchers could investigate consumers' cost perceptions over the whole lifecycle of a DGC and in dependence of the gift cards' expiration date.

Mitigating strategies of the seemingly negative effects of DGC usage for consumers could be a further topic of interest for future research. Many passengers in our airline data set booked their flight with another person. As pointed out by Cheng and Cryder (2018), analyzing joint decision-making in the context of mental accounting may raise interesting research questions. For example, whether joint decision-making leads to more rational decisions, or if DGC owners even persuade others into purchasing the same product or service.

References

Arkes, H. R., & Blumer, C. (1985). The Psychology of Sunk Costs. *Organizational Behavior and Human Decision Processes, 35*(February), 124–140.

Arkes, H. R., Joyner, C. A., Pezzo, M. V., Nash, J. G., Siegel-Jacobs, K., & Stone, E. (1994). The Psychology of Windfall Gains. *Organizational Behavior and Human Decision Processes, 59*(3), 331–347. https://doi.org/10.1006/OBHD.1994.1063

Chandran, S., & Morwitz, V. G. (2006). The Price of "Free"-dom: Consumer Sensitivity to Promotions with Negative Contextual Influences. *Journal of Consumer Research, 33*(3), 384–392. https://doi.org/10.1086/508439

Chatterjee, P., & Rose, R. L. (2012). Do Payment Mechanisms Change the Way Consumers Perceive Products? *Journal of Consumer Research, 38*(6), 1129–1139. https://doi.org/10.1086/661730

Cheng, A., & Cryder, C. (2018). Double Mental Discounting: When a Single Price Promotion Feels Twice as Nice. *Journal of Marketing Research, 55*(2), 226–238. https://doi.org/10.1509/jmr.15.0559

Comoreanu, A. (2017). Gift Card Market Size. https://wallethub.com/edu/gift-card-market-size/25590/

Dekimpe, Marnik, Hanssens, D. M., & Silva-Risso, J. M. (1998). Long-run effects of price promotions in scanner markets. *Journal of Econometrics, 89*(1–2), 269–291. https://doi.org/10.1016/S0304-4076(98)00064-5

Feinberg, R. A. (1986). Credit Cards as Spending Facilitating Stimuli: A Conditioning Interpretation. *Journal of Consumer Research, 13*(3), 348–356. https://doi.org/10.1086/209074

Gourville, J. T., & Soman, D. (1998). Payment Depreciation: The Behavioral Effects of Temporally Separating Payments From Consumption. *Journal of Consumer Research, 25*(2), 160–174. https://doi.org/10.1086/209533

Hardesty, D. M., & Bearden, W. O. (2003). Consumer evaluations of different promotion types and price presentations: The moderating role of promotional benefit level. *Journal of Retailing, 79*(1), 17–25. https://doi.org/10.1016/S0022-4359(03)00004-6

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford Publications. https://doi.org/978-1-60918-230-4

Heilman, C. M., Nakamoto, K., & Rao, A. G. (2003). Pleasant Surprises: Consumer Response to Unexpected In-Store Coupons. *Journal of Marketing Research, 39*(2), 242–252. https://doi.org/10.1509/jmkr.39.2.242.19081

Horne, D. (2007). Unredeemed gift cards and the problem of not providing customers with value. *Journal of Consumer Marketing, 24*(4), 192–193. https://doi.org/10.1108/07363760710755977

Kalwani, A. U., & Yim, C. K. (1992). Consumer Price and Promotion Expectations: An Experimental Study. *Journal of Marketing Research, 29*(1), 90–100. https://doi.org/10.2307/3172495

Kaul, A., & Wittink, D. R. (1995). Empirical Generalizations about the Impact of Advertising on Price Sensitivity and Price. *Marketing Science, 4*(3), 151–160.

Khouja, M., Pan, J., Ratchford, B. T., & Zhou, J. (2011). Analysis of free gift card program effectiveness. *Journal of Retailing, 87*(4), 444–461. https://doi.org/10.1016/J.JRETAI.2011.06.002

Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., & Loewenstein, G. (2007). Neural Predictors of Purchases. *Neuron, 53*(1), 147–156. https://doi.org/10.1016/J.NEURON.2006.11.010

Mela, C. F., Gupta, S., & Lehmann, D. R. (1997). The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. *Journal of Marketing Research, 34*(2), 248–261. https://doi.org/10.2307/3151862

Milkman, K. L., & Beshears, J. (2009). Mental accounting and small windfalls: Evidence from an online grocer. *Journal of Economic Behavior and Organization, 71*(2), 384–394. https://doi.org/10.1016/j.jebo.2009.04.007

Morewedge, C. K., Holtzman, L., & Epley, N. (2008). Unfixed Resources: Perceived Costs, Consumption, and the Accessible Account Effect. *Journal of Consumer Research, 34*(4), 459–467. https://doi.org/10.1086/518540

Offenberg, J. P. (2007). Markets: Gift Cards. *Journal of Economic Perspectives, 21*(2), 227–238. https://doi.org/10.1257/jep.21.2.227

Pauwels, K., Hanssens, D. M., & Siddarth, S. (2002). The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity. *Journal of Marketing Research, 39*(4), 421–439. https://doi.org/10.1509/jmkr.39.4.421.19114

Peer, E., Vosgerau, J., & Acquisti, A. (2014). Reputation as a sufficient condition for data quality on Amazon Mechanical Turk. *Behavior Research Methods, 46*(4), 1023–1031. https://doi.org/10.3758/s13428-013-0434-y

Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. *Marketing Science, 17*(1), 4–28. https://doi.org/10.1287/mksc.17.1.4

Prelec, D., & Simester, D. (2001). Always Leave Home without It: A Further Investigation of the Credit-Card Effect on Willingness to Pay. *Marketing Letters, 12*(1), 5–12.

Raghubir, P., & Srivastava, J. (2008). Monopoly Money: The Effect of Payment Coupling and Form on Spending Behavior. *Journal of Experimental Psychology: Applied, 14*(3), 213–225. https://doi.org/10.1037/1076-898X.14.3.213

Reinholtz, N., Bartels, D. M., & Parker, J. R. (2015). On the mental accounting of restricted-use funds: How gift cards change what people purchase. *Journal of Consumer Research, 42*(4), 596–614. https://doi.org/10.1093/jcr/ucv045

ResearchAndMarkets. (2018). Global Gift Cards Market Size, Market Share, Application Analysis, Regional Outlook, Growth Trends, Key Players, Competitive Strategies and Forecasts, 2018 To 2026. https://www.researchandmarkets.com/research/5ksr49/global_gift_cards?w=5

Shafir, E., & Thaler, R. H. (2006). Invest now, drink later, spend never: On the mental accounting of delayed consumption. *Journal of Economic Psychology, 27*(5), 694–712. https://doi.org/10.1016/j.joep.2006.05.008

Shefrin, H. M., & Thaler, R. H. (1988). The Behavioral Life-Cycle Hypothesis. *Economic Inquiry, 26*(4), 609–643. https://doi.org/10.1111/j.1465-7295.1988.tb01520.x

Shu, S. B., & Gneezy, A. (2010). Procrastination of Enjoyable Experiences. *Journal of Marketing Research, 47*(5), 933–944. https://doi.org/10.1509/jmkr.47.5.933

Soman, D. (2001). Effects of Payment Mechanism on Spending Behavior: The Role of Rehearsal and Immediacy of Payments. *Journal of Consumer Research, 27*(4), 460–474. https://doi.org/10.1086/319621

Soman, D. (2003). The Effect of Payment Transparency on Consumption: Quasi-Experiments from the Field. *Marketing Letters, 14*(2001), 173–183.

Statista. (2016). Nutzung von Coupons und Rabatten in Deutschland. https://de.statista.com/statistik/daten/studie/601789/umfrage/nutzung-von-coupons-und-rabatten-in-deutschland/

Technavio. (2018). Global Gift Card Market 2018-2022. https://www.technavio.com/report/global-gift-card-market-analysis-share-2018?utm_source=t10&utm_medium=bw&utm_campaign=businesswire

Thaler, R. H. (1980). Toward a Positive Theory of Consumer Choice. *Journal of Economic Behavior and Organization, 1*(March), 39–60.

Thaler, R. H. (1985). Mental Accounting and Consumer Choice. *Marketing Science, 4*(3), 199–214. https://doi.org/10.1287/mksc.4.3.199

Thaler, R. H., & Benartzi, S. (2004). Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy, 112*(February 2004), S164–S187. https://doi.org/10.1086/380085

Thaler, R. H., Kahneman, D., & Tversky, A. (2000). Mental Accounting Matters. Journal of Behavioral Decision Making, 206(September 1998), 241–268.

Thomas, L. M., & Dillenbeck, M. S. (2004). Best Used by Expiration Date. *Marketing Management, 13*(1), 53–56.

Thrun, M. C., Gehlert, T., & Ultsch, A. (2020). Analyzing the fine structure of distributions. *PLoS ONE, 15*(10 October), 1–20. https://doi.org/10.1371/journal.pone.0238835

Valentin, E. K., & Allred, A. T. (2012). Giving and getting gift cards. *Journal of Consumer Marketing, 29*(4), 271–279. https://doi.org/10.1108/07363761211237344

Vana, P., Lambrecht, A., & Bertini, M. (2018). Cashback Is Cash Forward: Delaying a Discount to Encourage Future Spending. *Journal of Marketing Research, 55*(6), 852–868. https://doi.org/10.2139/ssrn.2588611

White, R. (2006). Format Matters in the Mental Accounting of Funds: The Case of Gift Cards and Cash Gifts. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.948587

White, R. (2008). The Mental Accounting of Gift Card versus Cash Gift Funds. *Advances in Consumer Research, 35*, 722. https://login.libproxy.noctrl.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=buh&AN=35063876&site=eds-live

Yao, Q., & Chen, R. (2014). Gift Cards and Gifted Cash: The Impact of Fit between Gift Type and Message Construal. *Journal of Retailing, 90*(4), 481–492. https://doi.org/10.1016/j.jretai.2014.07.001

Zellermayer, O. (1996). The Pain of Paying. (Doctoral dissertation). Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA.

F. CURRICULUM VITAE

Curriculum Vitae

Name	Gianluca Scheidegger
Date of Birth	February 4th, 1992
Place of Birth	Schaffhausen, Switzerland

Education

01/2021 – present	**NYU Stern School of Business**, New York, USA Visiting Researcher
09/2020 – 12/2020	**HEC Paris**, Jouy-en-Josas, France Visiting Researcher
09/2017 – present	**University of St.Gallen**, St.Gallen, Switzerland Ph.D. in Marketing
09/2014 – 08/2016	**University of St.Gallen**, St.Gallen, Switzerland Master of Arts in Marketing, Services and Communication Management
08/2013 – 12/2013	**Singapore Management University,** Lee Kong Chian School of Business, Singapore Exchange Semester
09/2010 – 07/2014	**University of Zurich**, Zurich, Switzerland Bachelor of Arts in Economics and Business Administration

Work Experience

05/2017 – present	**Institute of Retail Management,** University of St.Gallen, Switzerland Research Associate
06/2016 – 03/2017	**Swiss International Air Lines,** Kloten, Switzerland Marketing Communication Campaigns
02/2014 – 06/2016 02/2012 – 07/2013	**Swissport International**, Kloten, Switzerland Passenger Service Agent
08/2012 – 07/2013	**Jungwacht Blauring,** Schaffhausen, Switzerland Office Manager
08/2007 – 07/2016	**Jungwacht Blauring - Voluntary**, Schaffhausen, Switzerland Group Leader, Editorial Team, Instructor