Three Paths to Brand Growth: New Product Introduction, Digital Advertising, and Crowdfunding

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Statement of Originality

This is to certify that:

i. This thesis constitutes my own work and that all material, which is not my own work, has been properly acknowledged;
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Acknowledgements

"*The Road goes ever on and on, down from the door where it began. Now far ahead the Road has gone, and I must follow, if I can. Pursuing it with eager feet, until it joins some larger way where many paths and errands meet. And whither then? I cannot say*."

-- J. R. R. Tolkien, The Lord of the Rings

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ABSTRACT

This thesis uses empirical techniques of dynamic modelling to examine three major means for brands to achieve sustainable growth, including new product introduction (NPI), digital advertising, and value co-creation with consumers through digital crowdfunding.

Essay 1 *(Chapter 2)* explores the impact of NPI on the performance volatility of the innovating and the competing brands in the CPG industry. Using a GARCH-in-VAR modelling approach, we find that NPI causes a long-term rise in sales volatility of all brands. Such volatility increase is especially significant for new brand entries, premium-priced and more innovative brands, and retailers with a larger assortment and those where private labels dominate. More importantly, NPI's impact through sales volatility on the sales level of brands is consistently positive. Findings from Essay 1 challenge marketers' conventional wisdom to curb volatility and instead highlight brands' potential to benefit from the market turbulence following an NPI.

Essay 2 *(Chapter 3)* investigates the effect of processing disfluency on consumers' decisions to click on digital display advertisements. With consumers flooded by digital ads, it is imperative for marketers to strike a balance between capturing consumer attention and keeping them unannoyed. A series of lab experiments combined with field data modelling using the Dynamic Factor Model indicate that processing disfluency can elicit consumer interest and desire to explore, leading to a higher willingness to click. Such disfluency does not cause consumer ad annoyance and can be induced by negative ad emotional appeals such as fear and sorrow.

Essay 3 (Chapter 4) studies investment dynamics between digital crowdfunding investors, who are also the future consumers of the fundraising venture. Recognizing the co-existence between more and less informed investors, our results show that large investments by informed investors are effective signals that positively influence subsequent investors' behaviours. Such an effect is strengthened by a higher level of social similarity between investors and the size of the deal. Our findings shed light on the asymmetric information flows from more to less informed investors, and the complementarity between different types of investors.

CHAPTER 1: Introduction

1.1 Motivations

Marketing research studies how business develops, promotes, and sells products and services. This requires the analysis of highly uncertain situations that involve making forecasts about future consumer behaviours and market scenarios. The digital revolution has offered researchers new metrics, new ability to collect data, which can be employed to identify and tackle new challenges, and deliver new insights (Cluley et al., 2020). This thesis uses empirical techniques of dynamic modelling to shed light on three complex areas, related respectively to new product introduction, branded advertising, and crowdfunding. These three areas correspond to different stages in the product life cycle and different levels of uncertainty.

To expand and achieve sustainable growth, brands rely on different marketing tools, including new product introductions (NPIs), display and banner advertising, search engine advertising, and gamification, to name a few (e.g., Demirci et al., 2014; Eisingerich et al., 2019; Pauwels et al., 2016; Veiga and Valletti, 2020). NPI is a pulsing marketing activity that has a great potential to boost the performance of a new brand, revitalize a mature brand, and, in the case of major successful market innovation, drastically restructure the competitive landscape of the market (Lamey et al., 2018; Sharma et al., 2018; Van Heerde et al., 2014). The extensive research on NPI has mostly focused on its impact on brand and product category performance levels, such as revenues and market share, and how NPI can inform brand strategies (Park et al., 2019; Pauwels et al., 2004). Nevertheless, besides performance levels, research has been relatively scarce on another primary consequence of NPI: turbulence, or volatility, of the brand and category performance.

Sales volatility refers to the degree of variations in sales over time and captures the rate at which it moves up or down (Raju, 2012; Tuli et al., 2010). It has been measured as the standard deviation and range of sales by previous studies (e.g., Fischer et al., 2016). NPI can be a major source of concern to managers if it results in a significant rise in sales volatility. For example, when Coca-Cola first launched its sugar-free line, Coke Zero, in 2006, the entire cola market experienced a period of high turbulence. Specifically, Coca-Cola, the innovating brand, launched several marketing programs to boost NP performance and brand success. Other brands of Coca-Cola reacted competitively to the NP; for example, Pepsi immediately lowered its price to defend sales against Coke Zero. Further, new brands like Red Bull entered the market with its cola drink slightly later in 2008. All these facts have led to intensified marketing competitions between brands following the NPI. Consumers were switching between product offerings and brands more frequently than usual and would stockpile during promotions, resulting in more frequent swings of brand sales and a higher level of performance volatility.

Sales volatility can be problematic because it leads to costly inventory management and difficulty in demand forecasting and strategic planning, to name a few (Esteban-Bravo et al., 2017; Fischer et al., 2016). Hence the conventional wisdom in the market has been that volatility is "bad" and should be curbed through effective interventions. However, research has not formally examined the validity of such a notion with concrete empirical evidence. What if there are positive demand spillovers from a rise in sales volatility around NPI? What if volatility is a prerequisite for permanent or long-term performance lifts that are unlikely to materialize under more stable market conditions? The answers to these questions are unclear since theoretical arguments for both a favorable and unfavorable effect of large sales swings on total demand can be forwarded. The first essay of this thesis (Chapter 2) studies whether and when NPI leads to a long-term rise in brand sales volatility and how the change in volatility influences brand sales.

While NPI is a robust engine for brands to grow and thrive, not all brands are able to develop or frequently launch new products. Nowadays, a more ubiquitous and intensive marketing tool adopted by almost all brands is digital advertising (Gordon et al., 2020). The total spending in the global digital advertising sector has reached $325 billion in 2019 and is projected to reach $389 billion by 2021. Marketers use digital display ads to capture consumer attention, after which brand awareness and recall, and conversions may be enhanced (Veiga and Valletti, 2020). Research along this line has concentrated on how marketers should refine ad creative elements and advertising tactics to shift consumer attention away from content browsing to the ads displayed alongside (Bruce et al., 2017; Ghosh and Stock, 2010; Maclnnis and Jaworski, 1989). Online pop-up ads and automatically played video ads are great examples of how hard digital ads try to catch consumers' spotlight (Edwards et al., 2002).

However, digital advertising performance is far from satisfactory and calls for further scrutiny since consumers nowadays are often “flooded by ads, most of which are not interesting or relevant” (Gordon et al., 2020). As consumers get more and more overfed by these advertisements, their annoyance and avoidance towards them have become a severe concern for marketers (e.g., Goldstein et al., 2014). For instance, too many repetitions of ad exposures can turn interested consumers annoyed and drive them away (Kronrod and Huber, 2019; Todri et al., 2020). Ads that are relevant (i.e., matching with website content) and obtrusive at the same time can backfire by raising consumers’ privacy concerns (Goldfarb and Tucker, 2011). To defend themselves against excessive exposure to digital advertising, consumers have even started to install ad blockers. Recent research shows that about 30% of the top 10,000 websites have detected usage of adblockers (Zhu et al., 2018). Therefore, how should display ads strike a healthy balance between directing consumers’ attention and keeping them unannoyed has become a challenge for contemporary digital marketers.

All these challenges have shed light on the subjective experience of processing fluency, namely the level of ease with which information can be processed (Alter and Oppenheimer, 2009; Schwara, 2004). More specifically, we are intrigued to explore the role of processing disfluency since consumers’ browsing experience needs to be “interrupted” to notice the ads alongside the contents. Extant advertising research has found creative elements such as color, contrast, symmetry, and direction of objects as antecedents of processing fluency (Forster et al., 2016; Landwehr et al., 2011; Leonhardt et al., 2015; Thompson and Ince, 2013). Emotional appeal is another critical ad creative element and engagement tactic that marketers use to influence consumer ad processing (Liu-Thompkins, 2019). While extant research has mostly focused on the difference between consumer response to rational versus emotional ad appeals (Guitart and Stremersch, 2020; Zhang et al., 2014; Xiang et al., 2019), we investigate the distinction between positive and negative appeals. Specifically, affect-cognition theories suggest that, compared with positive appeals, negative appeals capture more attention and induce deeper thinking of the audience, leading to more cognitive effort and a higher level of disfluency (Matovic et al., 2014).

Further, the impact of processing disfluency on consumer ad click-through is also unclear because theories on both a positive and a negative effect can be forwarded. On the one hand, people appreciate ease and convenience; hence fluent processing experiences should lead to a more favorable judgment (Reber and Unkelbach, 2010; Song and Schwarz, 2009). On the other hand, processing disfluency has been found to ignite audience interest, curiosity, and motivation to explore (Graf and Landwehr 2015; Walter et al., 2020). Therefore, the second essay of this thesis (Chapter 3) firstly explores the impact of negative (vs. positive) appeals of digital display ads on consumer processing disfluency. Next, it studies the effect of processing disfluency induced by negative ad appeal on consumer ad clicking, together with purchase intentions and ad and brand attitudes. Finally, this essay explores the potential moderating effect of the product/service category (hedonic vs. utilitarian) as an extension.

Finally, technology advancement has greatly facilitated and eased the process of innovation commercialization. The era of digitization has dramatically revolutionized the process of new product development, and introduction in terms of the role played by consumers (Moreau et al., 2020). Consumers nowadays can do far more than purchasing the products and services offered to them; instead, they are increasingly involved in the entire process of value creation and becoming value co-creators with the brands (van Osselae et al., 2020). For example, consumers can integrate their aspirations and pursuits for uniqueness into the product they purchase through customization (Franke and Piller, 2004). Digital interactive platforms such as crowdsourcing (Bayus, 2013) allow consumers to directly participate in the very early stage of product design by contributing creative ideas (Djelassi and Decoopman, 2013).

In recent years, equity crowdfunding has emerged as a new digital channel for young brands to co-create, co-fund, and co-commercialize new products with investors who are the future consumers (Bitterl and Schreier, 2018). The crowdfunding sector has rapidly grown from “alternative” to “mainstream” and has become a touchstone for most innovations. In 2018, 41,500 campaigns were launched on equity crowdfunding platforms globally, and this number is expected to grow to 64,500 by 2023. On these platforms, Investors jointly finance new ventures and, in return, receive an ownership stake (Ahlers et al., 2015). Besides financial resources, ventures also acquire intellectual contributions (e.g., product feedback) and word-of-mouth (Xu, 2018) from investors.

The composition of equity crowdfunding investors is hybrid, consisting of a mass number of ordinary individuals and a handful of professional investors such as business angels and venture capitalists (Rose et al., 2020; Wright et al., 2015). To understand how investors make funding decisions referring to different types of cues, prior studies have identified several entrepreneur-generated signals, such as their social, human, and intellectual capital, narrative style, and use of visual cues (Ahlers et al., 2015; Parhankangas and Renko, 2017; Vismara, 2016b). More importantly, other investors' investment behaviours can be another type of signal (i.e., investor-generated signal) that is even more credible since people tend to trust their peers more than the counterparty (Connelly et al., 2011; Vismara, 2016b). Nevertheless, how investors interpret and react to investor-generated signals is still under-exploited by extant research.

The third essay (Chapter 4) of this thesis fills in the literature gap by studying the information flow between equity crowdfunding investors. Recognizing investor heterogeneity, this essay first identifies angel investors from the crowds through a comprehensive set of criteria. It then studies whether and how high-contribution pledges (i.e., investments counting for a large proportion of the funding goal) made by angel investors can be credible signals that positively influence the amount of investment from subsequent investors. It also explores whether the social similarity between investors (i.e., investor type) and deal size (i.e., funding goal) exert moderation impacts on the signaling power. The findings of this essay can help entrepreneurs better understand investors' decision rationales and design more informed communication strategies by targeting influential investors.

1.2 Overview of Research Questions

This thesis consists of three essays exploring three topics. We summarize the research questions that we propose to examine in each essay as follows:

Topic 1: Brand performance volatilities induced by product innovations

In Essay 1 (Chapter 2), we focus on answering the following research questions:

i. What is the impact of new product introductions (NPIs) on brand sales volatility?

ii. What are the innovation-, brand-, and retailer-level drivers of changes in brand sales volatility induced by NPIs?

iii. What is the impact of volatility changes induced by NPIs on brand sales levels *over and above* NPI's direct impact on sales?

Topic 2: Emotional appeal of digital display ads and consumer processing fluency

In Essay 2 (Chapter 3), we aim to explore answers to the following research questions:

i. What is the impact of the negative (vs. positive) emotional appeal of digital display ads on consumer disfluency?
ii. What is the impact of consumer processing disfluency on consumer ad click-through behaviours?

Topic 3: Investor funding dynamics in equity crowdfunding

In Chapter 4, we aim to explore answers to the following research questions:

i. Do business angels co-exist with ordinary investors in equity crowdfunding?
ii. Are high-valued pledges made by professional investors effective signals so that they influence the amount of investments made by ordinary investors in equity crowdfunding?
iii. Do investor category and deal size impact the signaling effectiveness of high-valued pledges made by professional investors in equity crowdfunding?

1.3 Prior Research

1.3.1 Essay 1: NPI and brand performance volatility

The literature on NPI has been mostly focused on the direct impact of new product launches on brand and category level performance, such as sales (volumes), revenues, market shares, and cash flows. However, being described as "creative destruction", the impact of innovation introductions is far beyond what the vast literature has been exploiting. In fact, another critical aspect of innovation introduction on the market is to create turbulence or volatility. There is a small number of articles studying innovations from the perspective of volatility. For example, Esteban-Bravo et al. (2017) study the impact of the marketing mix (i.e., price and promotion) on brand sales volatility both in the short- and long-term. Fischer et al. (2016) focus on the impact of marketing mix on volatility in brand revenues and cash flows.

Performance turbulence caused by NPIs is the essence of brand survival and growth and is widely embraced by the literature in entrepreneurship, innovation, and strategic management (e.g., DiGregorio, 2005; Fischer et al., 2016; Hmieleski and Baron, 2008). Nevertheless, such turbulence has been mostly considered problematic and risky by marketers and managers. For instance, frequent ups and downs in performance figures make it hard for managers to evaluate the market response and product performance, adding further risk to planning in production and marketing investments (Rao and Bharadwaj, 2008). Brands with unstable earning patterns are typically deemed risky by investors who are mostly risk-averse, making it harder for them to acquire external financing (Minton and Schrand, 1999). Moreover, such a lack of external funding will further hinder the firm from investing in its future research and development and NPIs. It is also well known that the compensation and bonus scheme of firm executives, managers, and salespeople are all closely related to brand performance. However, volatile sales are typically considered undesirable and will harm their welfare.

From a retailer's perspective, a high level of sales volatility presents retailers with a severe challenge managing and planning for inventories and shelf spaces. Firstly, retailers need to hedge themselves against the risk of stock-outs since consumers usually do not have store-specific loyalty and stickiness and might easily switch to other stores in such situations (Campo et al., 2003). Storing a large amount of inventory can be costly, especially if the product by nature is perishable. Secondly, to boost sales, retailers often carefully manage and optimize their shelf spaces so that popular products and brands are placed in a more attention-grabbing and accessible area (Davies, 1994). Given substantial sales volatility, retailers will have to frequently rearrange their shelves, which can be quite costly and even wrong. Therefore, volatility in sales has been generally deemed as risky and dangerous, and that managers and retailers have been advised to take marketing and operation interventions to curb it and gauge for a smoother and steadier sales pattern to be successful and secured (Esteban-Bravo et al., 2017).

However, to our best knowledge, while these studies all take the assumption that volatility is something that should be avoided, none of them have stepped further and formally examined the effect of volatility on brand performance. Chapter 2 of this thesis aims at filling in this gap in the literature by modelling the impact of new product introductions on (both short- and long-term) brand sales volatilities and the impact of such change in volatilities on the level of brand sales.

1.3.2 Essay 2: Emotional appeal, consumer processing disfluency and clicking of digital display Ads

Digital advertising is a ubiquitous marketing device through which brands capture consumer attention, engage with consumers, and incentivize click-throughs and conversions (i.e., adoptions or purchases). However, because the volume of digital advertising has massively increased over the past decades, consumers started to experience information overload, which reduced the effectiveness and return on investments of these ads. Consequently, marketers have come up with several strategies to make their ads stand out through a high level of ad repetitions, targeting relevance (i.e., matching between contents of the ad and the webpage), and obtrusiveness, to name a few (Todri et al., 2020; Goldfarb and Tucker, 2011; Kronrod and Huber, 2019). Nevertheless, attention-grabbing techniques do not always generate ideal outcomes and instead may easily get consumers exhausted, irritated, and annoyed. Further, consumers have started to install adblockers to actively avoid digital ads (Gordon et al., 2020).

In the search for effective advertising strategies that attract consumers' attention and keep them unannoyed at the same time, a recent line of research has focused on the subjective experience of processing fluency. Processing fluency refers to the subjective experience of ease or difficulty with which individuals process a stimulus; it affects individuals' perceptions and responses to stimulus (see Alter and Oppenheimer, 2009, for a systematic literature review). The perception of fluency can originate from different stimuli such as visual, linguistic, and olfactory cues (Herrmann et al., 2013; Luffarelli et al., 2019a). Based on the definition of processing fluency, stimuli that require more cognitive effort to process should lead to a lower (higher) level of fluency (disfluency). For example, when reading linguistically complex texts (e.g., texts displayed with low readability or texts that are difficult to comprehend due to lexical, rhetoric, or semantic complexity), one needs to exert much more cognitive effort, which results in more disfluency (Oppenheimer, 2006). Brand logos that are information-rich with high descriptiveness and concrete visual details are easier for people to understand, memorize, and recall (Luffarelli et al., 2019a). Moreover, when stimuli are designed or presented congruently with social norms or with one's prior knowledge schema, people tend to find them more fluent in processing due to conceptual and cognitive priming, salience, and familiarity (Humphreys et al., 2020; Puccinelli et al., 2015; Winkielman et al., 2006).

While processing fluency relates closely to ease and convenience that people seek and appreciate, it does not always lead to a positive consequence. Specifically, processing fluency has been found to generate positive and negative effects on an individual's attitude and decision-making regarding a stimulus. On the positive side, prior research indicates that people tend to feel that a more fluent visual stimulus is more aesthetically appealing pleasing (Alter and

Oppenheimer, 2009; Song and Schwarz, 2008). A brand with a logo and text descriptions that are processed more fluently tends to be judged as more authentic because people perceive fluent stimuli as more credible, trustworthy, and reliable (Morhart et al., 2015). Stimuli that are designed and presented in compliance with prototype or schema are judged more positively and elicit more conversions (Chae and Hoegg, 2013; Graf et al., 2018; Landwehr et al., 2013; Reber et al., 2004). Similarly, video advertising congruent with audiences' psychological states is favored (Puccinelli et al., 2015).

On the contrary, other research has discovered the negative impact of processing fluency (or the positive effect of processing disfluency). For instance, visual stimuli that exhibit more contrast with its surrounding have stronger signal power due to visual salience and attention attraction (Aribarg and Schwartz, 2020; Pieters and Wedel, 2004; Van der Lan et al., 2008). In the context of retailing, product arrangements that are not systematic or familiar to consumers cause a greater level of processing disfluency, which results in even more product trials and adoptions. Processing disfluency can lead consumers to evaluate a higher number of alternatives, elicit their inference of specialness, interests, and importance of a task (Graf and Landwehr, 2015; Pocheptsova et al., 2010; Walter et al., 2020).

However, very few prior studies focus on the antecedents and consequences of people's subjective experience of fluency while they are exposed to digital display ads. While findings from previous studies explored a few sources of processing fluency (e.g., color, language, logo, and product direction of an ad), almost no research has examined the impact of positive and negative emotional appeals. Furthermore, the consequence of processing fluency, namely its effect on consumer willingness to click on an ad, to purchase, and consumer ad and brand attitudes are also under-explored. Chapter 3 of this thesis fills in these literature gaps by studying the antecedents and consequences of processing fluency in the context of digital display ads.

1.3.3 Essay 3: Investor dynamics and information flows in equity crowdfunding

Equity crowdfunding is a subcategory of crowdfunding, referring to "a form of financing in which entrepreneurs make an open call to sell a specified amount of equity or bond-like shares in a company on the Internet, hoping to attract a large group of investors" (Ahlers et al., 2015). As digital equity crowdfunding platforms continue to grow, an increasing number of early-stage entrepreneurial ventures turn to these platforms to raise capital (Zhang et al., 2015).

Crowdfunding functions beyond a financing platform since entrepreneurs also receive intellectual (e.g., product feedback, see Xu, 2018) and social contributions (e.g., free word-of-mouth, Stanko and Henard, 2016) from investors. Consequently, recently marketing researchers have started to study (equity) crowdfunding as a digital marketing tool that new brands use to reach investors who are meanwhile future consumers (Belleflamme et al., 2014). For example, research has investigated fundraising entrepreneurs' pricing and product offering strategies (Hu et al., 2015). Others study how entrepreneurs should craft the campaigning webpage using different media forms (e.g., texts, images, and videos) to signal their innovativeness, passion, and prosocial attitudes (e.g., Dai and Zhang, 2019; Li et al., 2017; Mahmood et al., 2019; Simpson et al., 2020).

However, just like any other entrepreneurial financing channels, equity crowdfunding suffers from serious information asymmetry problems between the fundraising ventures and the investors (Vismara, 2016b). This is mainly due to the short fundraising time frames (30 to 60 days), the early stage of ventures, and limited offline contact with entrepreneurs (Wang et al., 2019). Therefore, in addition to grabbing investor attention through multi-media digital campaigning, it is also imperative to understand how entrepreneurs can help investors overcome their suspicions about the innovation quality through signaling (Connelly et al., 2011). Research along this line has studied several financial and non-financial information cues, including founding team qualifications, equity share offered to the investors, and linguistics used in the venture descriptions, to name a few (Ahlers et al., 2015; Vismara, 2016a).

While research on entrepreneurs is quite rich, that on investors is relatively scarce. Extant studies have shed some light on the heterogeneity among crowdfunding investors regarding their investment experience, expertise, and motivation. For example, Kim and Viswanathan (2018) categorized investors into "experts" and "crowds", while Xiang et al. (2019) divide investors into "consumer backers" and "investor backers". Due to its investment model, equity crowdfunding attracts large and professional investors like business angels who seek diversity and convenience of investments (BBB and UKBAA, 2017). Angels are generally defined as "high net worth individuals who invest their own money, either alone or with others, directly in unquoted businesses in which there is no family connection" (Mason et al., 2016, p.322). They differ significantly from ordinary individuals (i.e., "the crowd") in terms of wealth, investment experience, expertise, and investment behaviours (Landström and Mason, 2016; Wright et al., 2015). Researchers need to recognize the co-existence between angels and the crowd since their distinction may substantially impact the way investors receive, interpret, and react to signals. Therefore, Chapter 4 of this thesis studies how investors respond to signals generated by other investors in equity crowdfunding.

1.4 Data Overview

The three essays included in this thesis benefit from rich and comprehensive observational and experimental data.

Essay 1 (Chapter 2) studies sales volatility in relation to NPI in the grocery business. We obtained consumer panel data from GfK Germany, including new products launched in the German market across nine frequently purchased CPG categories: bath & shower gel, biscuits, cola, coffee, crisps, diapers, razors, tea, and yoghurt. The data spanned between January 2005 and December 2012 (417 weeks) and was available for purchase information at the six largest German retail chains. The retailers are Aldi, Edeka, Kaufland, Lidl, Real, and Rewe. Following a rigorous screening process, we were able to identify a total of 182 NPs, consisting of 171 sub-brands introduced by 45 established manufacturer brands and 11 new brands. Our final analysis included 214 brand-retailer combinations (models).

Essay 2 (Chapter 3) studies consumer clicking behaviours on digital display advertising using a combination of experimental and observational data. We ran a series of lab experiments first to examine the mediating role of processing disfluency in linking negative emotional appeals and consumer clicking intentions on digital display ads. Using Amazon MTurk, we had responses from 120, 106, and 106 participants for the preparatory study and study 1 and 2, respectively. Our field study is enabled by a unique dataset of ad impression and clicking behaviour of households in the Netherland during the time period from 14th October 2016 to 31st March 2017. The dataset captures a display ad network and nine of its clients coming from seven B2C industries, including travel, financial service, department stores, holiday villages, printing service, grocery retailer, and education providers. After data sanitization and aggregation, the final data consists of 80,345 observations (household-minute level) of 655 households across 324 unique ad creatives.

Essay 3 (Chapter 4) studies the investment dynamics of equity crowdfunding investors. We obtained a proprietary dataset on investment data of 50,999 unique investors across 1,151 unique campaigns from July 2012 to August 2017 on one of the UK's leading ECF platforms[1]. Investment data cover fundraising ventures across 13 sectors, with the most popular being financial services, food & drink, digital media, entertainment, and technology.

1.5 Methodology Overview

This section gives a brief overview of two modelling approaches used in this thesis[2] (technical details can be found in corresponding chapters)**:** Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model and Dynamic Factor Model (DFM). **Specifically,** Chapter 2 uses a GARCH-in-VAR model to study the impact of NPI on brand sales volatility and the effect of sales volatility on sales level, while DFM is adopted in Chapter 3 to validate the impact of processing disfluency on consumer ad clicking.

1.5.1 Generalized Auto Regressive Constant Heteroskedasticity Models

Time-series data can be described from many angles, among which the mean and the volatility are the two most typical metrics. While the mean (or expected value) of a time series captures the average level of the data, variance captures the turbulence level, namely the level of fluctuation of the series around its mean (Franses and van Dijk, 2000).

GARCH model is the generalized version of the Auto Regressive Constant Heteroskedasticity (ARCH) model, which was firstly proposed by Engle (1982). GARCH model incorporates the dynamics of data volatility by recognizing a time-varying conditional variance (instead of a constant conditional variance over time). It first determines the conditional mean of a series and then the volatility. It estimates conditional variances of data series in an explicit way, similar to how conditional mean is estimated by an autoregressive moving average (ARMA) model. GARCH model has been frequently applied in the finance literature to model economic regimes associated with different levels of volatilities in data. It was only recently the model starts to get adopted by marketing literature to study volatilities in various metrics such as brand sales, category sales, and user-generated content (UGC) volumes on social media (Esteban-Bravo et al., 2017; van Dieijen et al., 2020).

[1] A Non-Disclosure Agreement prevents us from disclosing the identity of the platform.
[2] While other methods such as mediation analysis via PROCESS models (Hayes, 2017) and fixed effects ordinary least square regressions are also used in this thesis, we emphasize on giving an overview of GARCH and DFM models.

GARCH model is the appropriate modelling approach for Chapter 2[3] because the chapter's foundation is that volatility in sales is not constant but varies over time. Specifically, we expect that new product introductions significantly increase brand sales volatility not only contemporaneously but also in the long run. GARCH model enables us to explicitly evaluate the change in brand sales volatility via estimating conditional covariance of brand sales equation (see Chapter 2 for more details) before and after NPIs. Further, incorporating estimates from GARCH model into VAR model enables us to explicitly measure the impact of innovation-induced volatilities on the level of weekly brand sales.

1.5.2 Dynamic Factor Model

Dynamic Factor Model (DFM) is a powerful statistical technique to reduce data dimensions in a parsimonious manner (for comprehensive surveys on the methodology, please refer to Barigozzi, 2018; Bai and Ng, 2008; Stock and Watson, 2016). It was first introduced in the field of psychology (Spearman, 1904) to model the cognitive abilities of an individual as an unobserved factor. Later, DFM was applied in macroeconomics research to capture the co-movement of time series under the impact of unobservable factors. For example, Burns and Mitchell (1946) are among the first to use DFM to model the effect of the business cycle, which "consists of expansions occurring at about the same time in many economic activities".

DFM is considered an appropriate modelling approach for analyzing field data in Chapter 3 for the following reasons. First, we require a model that incorporates the intermediate factor, namely processing disfluency, as an unobservable factor and links the unobservable construct to observed consumer ad impressions and clicking. Second, the model needs to filter out the noise in measuring the unobserved factor to avoid inconsistent estimates and wrong inferences. Third, we need to model consumer disfluency as a dynamic construct that gets updated over time. Finally, consumers' processing disfluency is likely endogenous to ad impressions and clicking behaviours. Thus, we model the unobserved construct and consumer ad impressions and clicking

[3] There are quite a few variations of GARCH model, including Exponential GARCH (EGARCH), Integrated GARCH (IGARCH), Constant Conditional Correlation GARCH (CCC-GARCH), Dynamic Conditional Correlation GARCH (DCC-GARCH), and Varying Conditional Correlation GARCH (VCC-GARCH), to name a few. In this thesis, we applied the multivariate CCC-GARCH model in Chapter 2. For specific reasons why we consider CCC-GARCH as particularly suitable for this research, please refer to Chapter 2.

as having a vector autoregressive process. Therefore, following Bruce et al. (2012), we specify a DFM for this essay.

1.6 An Overview of Theoretical and Practical Contributions

Overall, an overarching topic that bridges the three essays is how brands at different stages along their life cycle can achieve growth through a better understanding of consumer information processing under uncertainty. A seed-stage brand that raise funds for business materialization at equity crowdfunding platform is faced with information asymmetry between itself and target investors. To reinforce investor confidence by reducing their uncertainty towards business quality, we study how investors make funding decisions through a theoretical lens of signaling. Essay 3 studies how fundraising brands can increase success likelihood and secure future growth by understanding investors' interpretations and reactions to behaviors of their predecessors. At the introduction and (or) growth stage, brands usually launch new products to further strengthen market position, improve business performance, and even revitalize themselves for new growth. Yet consumers are faced with the uncertainty in new product quality and attractiveness. Essay 1 investigates, at an aggregate level, consumers' reactions to uncertainties involved in new products introduced by CPG brands. Specifically, with a new product added to the market, consumers tend to switch between their habitual choices and the new offering intensively or even drastically change their purchase. Essay 1 hence explores whether consumers' switching, which in combination results in brand-level performance turbulence, will benefit or harm a brand. Finally, to boost awareness and performance, brands at especially later stages of their life cycles tend to engage in advertising, especially online advertising in the age of digitization. However, the effectiveness of online advertising is still low and it remains a myth how consumers process and react to information cues in the ads. Essay 2 studies consumers' processing of emotional appeal in digital display advertisements. We investigate whether negative appeal leads to deeper information processing hence higher processing disfluency, and whether such disfluency can turn into a higher likelihood of ad click-through.

1.6.1 Implications for Theory

This thesis contributes to the literature on new product introduction (NPI) and performance volatilities (Chapter 2), digital advertising (Chapter 3), and digital crowdfunding and marketing communication (Chapter 4). While theoretical contributions will be discussed in detail in each chapter, here we present a general overview.

Chapter 2 is among the first studies that investigate the source and impact of performance volatility in marketing. More importantly, the findings challenge prior research along this line (e.g., Estaban-Bravo et al., 2017; Fscher et al., 2016). We contribute to the literature by establishing and quantifying the long-term impact of NPIs on brand sales volatility and explicitly modelling the impact of volatility on brand sales. While extant research has mostly focused on strategies for brands and retailers to curb volatilities, our findings address that despite the adverse consequences in operation and production, sales volatility actually has a robust positive impact on brand sales in the CPG sector. Secondly, Chapter 2 is among the first in the literature to explore the impact of innovation-, brand-, and retailer-level factors on the level of change in sales volatility due to NPI. Therefore, we contribute to the literature by uncovering several critical boundary conditions for the relationships we find. Finally, by analyzing brand innovations from nine CPG categories and six major retail chains, the findings and implications derived from Chapter 2 may be generalizable to the entire CPG sector.

The contributions to the literature of Chapter 3 are three-fold. Firstly, we contribute to the literature on the antecedent of processing fluency in the digital advertising context. Specifically, to our best knowledge, no studies have formally examined how display ads' emotional appeals influence the level of ease that they are processed. Building on affect-cognition theory, we uncover the association between negative ad appeals and consumer processing disfluency. Secondly, given that theoretical arguments for a positive and negative impact of processing fluency exist, our study contributes to the literature by finding the positive impact of disfluency for display ads. Finally, we are among the first to adopt DFM to explicitly model consumers' subjective experience of processing fluency as an unobservable, dynamic, and endogenous factor that co-moves and interacts with observable behaviours.

Finally, Chapter 4 contributes to the literature in three ways. Firstly, we are among the first papers to explicitly recognize investor heterogeneity and identify angel investors from general crowds using a combination of demographic and behavioural criteria. Secondly, this chapter highlights the disproportionally high signaling effect of large investments made by angel investors, together with its boundary conditions. While prior research has mostly studied entrepreneurs' signals, this chapter investigates how signals from their peers' influence investor's funding behaviour. We hence extend the research on the dynamics of equity crowdfunding from the demand side (i.e., entrepreneurs) to the supply side (i.e., investors). Finally, this chapter combines insights from information economics, sociology, and entrepreneurship, hence addressing the call for multidisciplinary crowdfunding research (McKenny et al., 2017).

1.6.2 Implications for Practice

All three essays in this thesis are motivated and informed by real business challenges that marketers, managers, retailers, and advertisers are faced with in both online and offline markets. Consequently, our research findings have rich and critical implications for practitioners.

Research findings from Essay 1 (Chapter 2) challenge conventional and prevalent wisdom about performance volatility in the CPG industry. Instead of taking marketing interventions right away to curb volatility induced by NPIs, our results suggest managers conduct a cost-benefit analysis before taking any actions towards volatility. Managers should weigh the gain from sales levels due to volatility increase against the loss due to inefficiencies and costs in operation and production. Furthermore, managers may not be overly defensive towards innovation launches from their competitors since the turbulence created by competitors may benefit their own sales. Finally, when estimating the possible gain in sales owing to NPI-induced volatility, brand managers are recommended to take several innovation-, brand-, and retailer-level factors highlighted in our study into consideration. Managers should actively monitor the performance of the innovation, the brand's position in the market, and the assortment composition at the retailer from time to time to benefit the most from the NPI.

Essay 2 (Chapter 3) highlights the importance of processing disfluency in influencing consumers' reactions to digital display ads. Our results imply that instead of a smooth experience, a certain level of disfluency, or "bumpiness" in consumers' processing journey, can be beneficial. To improve return on advertising investments, marketers can make proper use of negative emotional appeals (e.g., fear, anxiety, anger). Ad creative elements that require slightly more cognitive efforts to process or are slightly against consumers' cognitive schema, expectation, and experience can shift consumers' attention towards the ads while browsing web contents. More importantly, such processing disfluency will not annoy consumers and induce ad avoidance and blocking, but instead elicit their interests and willingness to explore, leading to ad clicking. While disfluency induced by negative ad appeals seems effective for digital marketers, one should also keep in mind the trade-off between short- and long-run benefits of brands. Specifically, our experimental results indicate that disfluency may lead to a negative brand attitude, which is supposed to endanger brand image and equity in the long run.

Finally, findings from Essay 3 (Chapter 4) have implications for fundraising entrepreneurs and policymakers. For example, entrepreneurs are recommended to reach out to large and reputational angel investors from time to time and secure their investments. Contributions from angels can then exert the signaling power to attract more funding from subsequent angel investors and the crowd. Further, given that the signal's effect depends on the size of the contribution and decays over time, entrepreneurs should keep such effort throughout the fundraising period. From a policy perspective, regulators should advocate standardized information collection across platforms via in-depth questionnaires on investors' financial acumen, experience, qualifications, and wealth to categorize investors. More importantly, we help address the value of using the behaviour-based investor categorization we employ in the study. Finally, platforms should educate investors about the investment risks and the possibility of fraudulent identities of other investors. Stringent due diligence can help ensure that no false signals are sent to mislead the crowd. Overall, these implications support regulators' recent focus on tightening the regulatory framework for platforms in the crowdfunding sector (FCA, 2018).

CHAPTER 2

Essay 1: Market Turbulence Following a New Product Introduction: Is It Really So Bad?

Abstract

In spite of its beneficial effect on brand performance levels, the launch of a new product can be an important source of concern to managers if it results in higher uncertainty through a rise in sales volatility for their brands. While undesirable from an operational perspective, arguments for both a favorable and unfavorable effect of large sales swings on future consumer demand can be forwarded, making it unclear if, and for which brands, sales volatility around new product launch is good or bad.

Brand-level sales data from nine Consumer Packaged Goods categories in six leading German retailers are collected to study if and how brand sales volatility at the retailer changes after a new product launch. Using a multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, this study confirms that there is a significant and persistent rise in sales volatility after launch in most instances, not just for the innovating brand but also for its competing offerings. This rise is not the same across brands and innovations. Entry by a new brand in the category, for instance, raises sales volatility even more than own brand innovations, while a competing brand entry has the lowest impact, except when it is highly successful. The rise in sales volatility is also higher for premium-priced and more innovative brands, and in retailers with a larger assortment and those where private labels dominate. Interestingly, when these volatility estimates are incorporated back into the VAR model, the results support that higher sales volatility following launch is even rewarded, and thus, associated with larger brand sales levels afterwards. Hence, the common reaction by managers to (try to) smooth out large sales fluctuations may not always be warranted.

2.1 Introduction

Developing and launching innovation has been a key firm objective to prosper in virtually every industry. Manufacturers continue to treat innovations as their top priority in order to enhance sales performance and further improve their competitive position (Sorescu and Spanjol 2008). Also, retailers embrace innovations to offer their customers an attractive assortment with the latest innovations and to enhance further store image and success (Lamey et al., 2018). But apart from their potential financial benefits, innovations can be an important source of concern to both manufacturers and retailers as they are frequently associated with large swings and unstable sales patterns following a launch. Not only the innovating brand but also competing brands can be affected. Indeed, innovations have the potential to boost retailer activity, resulting in large sales booms followed by sudden crashes that result in more 'volatile' sales patterns for its brands. Van Heerde, Mela, and Manchanda (2004) already established that new product introductions (NPIs) in the Consumer-Packaged Goods (CPG) business stimulate brand switching, as consumer preferences can shift significantly, and shoppers are 'shaken out' of their habitual buying patterns. Moreover, big marketing spending bursts around launch time, both by the innovator and its competitors that react to it, have been associated with sudden steep sales swings where large peaks and drops alternate (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017; Fischer, Shin, and Hanssens 2016; Vakratsas 2008).

Sales volatility refers to the degree of variation in sales over time and captures the rate at which it moves up or down around its long-term mean or growth pattern (Raju 2012; Tuli, Bharadwaj, and Kohli 2010).[4] It reflects the uncertainty of customer demand, and hence, firms with higher sales volatility are also viewed as riskier and are valued less (Miller 2006; Srivastava, Shervani, and Fahey 1999). For *retailers*, more volatile sales patterns for its brands complicate inventory activities tremendously. Indeed, costly inefficiencies accrue due to excessive or obsolete inventories; the need to increase the safety stock or 'inventory buffer' to hedge against more frequent stock-outs increases; and lost sales occur in case of perishable products (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017). Large swings in revenues and cash flows may also harm retailers' financial performance as it becomes harder to pay invoices and cover their fixed costs in time, while retailers miss out more often on discounts for advanced

[4] Volatility reflect the fluctuations around the series' long-term pattern that may or may not be constant over time. To illustrate, suppose the average weekly sales for a brand determined over an entire year is $100 (=total sales of $5,200/52 weeks), with sales volatility or week-to-week fluctuations in brand sales of 10% before new product entry (i.e., most weeks have sales between $90 and $110). This sales volatility may rise to 20% after new product entry (with week sales between $80-$120). So while the long-term sales pattern is fixed at $100 a week in both periods, the week-to-week variation in sales has changed.

or prepayments, for instance. Also, *manufacturers* eschew volatility in brand sales because unstable demand patterns increase operational complexity and production costs rise disproportionally with large swings, known as the 'bullwhip' effect (Cachon, Randall, and Schmidt 2007; Lee, Padmanabhan, and Whang 1997). The economic inefficiencies from unstable sales and the adverse investor evaluation of volatile cash flows increase the cost of accessing external capital to fund temporary cash shortfalls and other activities (Fischer, Shin, and Hanssens 2016). Moreover, larger sales and performance swings have been shown to hamper suppliers' R&D investments and to discourage future innovation activity because firms are unwilling to rely on (more) costly external capital to finance R&D and advertising (Minton and Schrand 1999).

In light of these adverse operational and financial consequences, earlier studies propagate to mitigate or 'curb' sales volatility and encourage managers to smooth the sales fluctuations following a major marketing intervention (e.g., Fischer, Shin, and Hanssens 2016; Esteban-Bravo, Vidal-Sanz, and Yildirim 2017). Also, practitioners openly plead to manage revenue volatility when an industry is confronted with higher levels of demand uncertainty (Dyer, Furr, and Lefrandt 2014, Gartner 2020) and to reduce frequent price promotions that are known to foster excessive sales swings, especially in retailing (Marketing Week 2014). But what if there are positive demand spillovers from a rise in sales volatility around NPI in the form of higher sales returns or steeper growth? Perhaps volatility is a prerequisite for a permanent performance lift that is unlikely to materialize under more stable market conditions. Further, will innovations always drive up sales volatility, and what brands outside the innovating brand are affected most?

This article examines the brand sales dynamics that result from the introduction of new products in the German CPG market. In particular, we assess to what extent a large set of 182 innovations launched across nine different CPG categories changes sales volatility for the innovating brand as well as its main competitors at the retailer. At the same time, we address whether these swings in brand sales after NPI contribute to (positive effect), or instead inhibit (negative effect) brand 'cumulative' performance levels afterwards (i.e., brand sales summed across all future periods), or whether it merely shift sales over time, without any impact on total sales levels (no effect). Unravelling this volatility-performance relationship has not only fundamental academic value but also clear management implications. If larger sales swings inhibit brand performance, managers should actively use their marketing instruments to diminish or avoid sales swings and smooth sales volatility after product launch. In contrast, if sales volatility has positive demand effects associated with higher total sales levels and growth, advice from practitioners and from earlier research by, e.g., Fischer, Shin, and Hanssens (2016), Vakratsas (2008), or Esteban-Bravo, Vidal-Sanz, and Yildirim (2017) to dampen these sales fluctuations may not be (fully) warranted. Finally, we further explore what factors drive the observed changes in sales volatility after entry across competing brands. Insights on what innovations affect sales patterns for what brands at a store can guide manufacturers and retailers in their production and inventory activities when new products disturb the common market operations and raise sales uncertainty.

2.2 Background Literature

Table 2.1 provides an overview of marketing studies that evaluated volatility in brand sales or revenues in response to marketing actions. Traditionally, marketing's focus has been on the effect of marketing actions on sales and performance levels, but the literature is surprisingly silent about the volatility in sales in relation to strategic marketing decisions.[5] Thus far, only few marketing studies evaluated volatility in sales or revenues in response to marketing actions. We refer to Table 1 in a recent publication by Esteban-Bravo, Vidal-Sanz, and Yildirim (2017) for an overview of the literature. Some studies indeed found that marketing actions can change volatility in brand and market sales. Raju (1992) finds that the magnitude and frequency of price discounts partially explain variability in weekly category sales. Vakratsas (2008) extends these results and shows that advertising, pricing, and distribution activity can significantly influence monthly market share volatility in the SUV market, while their relationship with market share levels of the respective brands is far more modest. More recently, Fischer, Shin, and Hanssens (2016) link combined marketing spending levels and volatility to quarterly unit sales for prescription drugs, while Esteban-Bravo, Vidal-Sanz, and Yildirim (2017) show that brand prices and promotional actions can be used to manage volatility in grocery sales, although not all products show a change in volatility following a price adjustment. Quite strikingly, these studies all recommend strategies for brand managers or retailers on how to curb volatility in sales in order to enhance firm performance.

The current study differs from earlier work on three key aspects. First, previous research focused on volatility caused by common, often more gradual changes in price, promotions, advertising actions, and/or distribution coverage on own brand or category sales,

[5] Marketing literature on volatility most often takes a financial focus, linking marketing variables such as marketing mix instruments, customer satisfaction, and channel relationships to financial performance rather than sales (see e.g., Srivastava, Shervani, and Fahey 1998; Gruca and Rego 2005; Fornell, Rust, and Dekimpe 2010; Tuli and Bharadwaj 2009; Tarasi et al. 2011).

while thus far, the impact of launching a new product on sales volatility has been largely overlooked. Innovations often present a more drastic ‘shock’ in the market with the potential to alter or disrupt the current market significantly. Van Heerde, Mela, and Manchanda (2004), for instance, confirm that new products can alter the market structure and (temporarily) increase the sales variance around the time of introduction. As a result, innovations have the potential to generate ‘turbulence’ characterized by increased sales variability at the brand and retailer level (Bronnenberg, Mahajan, and Vanhonacker 2000). However, the study by van Heerde, Mela, and Manchanda (2004) is mainly concerned about the brands’ market performance level, while the observed market volatility could not be linked to individual brands or retailers. Based on data from a broad set of brands and retailers, this study further explores if NPIs systematically change volatility in brand sales and what existing brands and retailers are most sensitive to.

Second, while earlier work merely established if sales volatility changes, we further evaluate when and why this occurs. Not all innovations have the same potential to disrupt the market and boost sales volatility among existing brands. Our analyses of a large set of innovations adopted by leading German retail chains allow us to link the observed rise in volatility to a set of drivers to understand better when and why new products influence sales volatility among established brands.

Finally, earlier studies mainly took a stand that sales volatility is harmful and managers should avoid or try to smooth it. Although we acknowledge the operational costs and inefficiencies that arise when sales swings get amplified, no study has considered the demand-side effects, i.e., whether there are also benefits in the form of higher sales levels and/or growth acceleration. Thus, in contrast to the widely held view that sales volatility is bad, we take a more nuanced or balanced perspective and formally explore if sales volatility following an NPI has positive or negative sales spillover effects. In this study, we theorize and test whether sales volatility due to an NPI can contribute to higher or lower future brand sales levels at the retailer.

2.3 Research Framework

While the effect of new product entry on brand and category sales *levels* has been well-documented in the literature (e.g., Nijs et al. 2001; Sorescu and Spanjol 2008), its impact on sales *volatility* received far less attention. We propose that an NPI affects sales volatility for the innovating brand and its competing (branded and private label) offerings at the retailer.

Table 2.1: Literature Summary

					Focus		Impact studied			
Article	**Research objective**	**Key marketing variables (IVs)**	**Performance variable (DV)**	**Main findings**	**NPI**	**Retailer**	**IV → own brand volatility**	**IV → competing brand volatility**	**IV → performance**	**Volatility → performance**
van Heerde et al. (2004)	How do product innovations change market dynamics?	Price, promotion and product innovation	Own and competing brand sales	*A major innovation increases brand similarities, decreases brand differentiation for the existing brands, and increases uncertainty in sales response.	✓	✗	✓	✓	✓	✗
Vakratsas (2008)	How do marketing mix actions affect market share volatility?	Advertising, price and distribution	Market share, market share volatility	* Market share volatility is influenced by advertising, pricing and distribution decisions.	✗	✗	✓	✗	✗	✗
Fischer et al. (2016)	How are revenues and cash-flow volatility influenced by own and competitive marketing spending volatility, by the level of marketing spending, by the responsiveness of own marketing spending, and by competitive reactivity?	Aggregate marketing expenditures on detailing, journal advertising and other media communications, competitive marketing expenditures	Own brand sales, revenues, cash flows	*Volatile marketing spending can have negative financial side effects such as greater financing costs or higher opportunity costs of cash holdings. *Common volatility-increasing marketing practices such as advertising pulsing may be effective at the top-line, but could be ineffective after all costs are taken into account.	✗	✗	✓	✗	✓	✗
Esteban-Bravo et al. (2017)	What is the impact of marketing mix actions on sales volatility both in the short- and long-term?	Price and promotion	Own brand sales	* Price and promotions affect sales and vice versa in both mean and volatility. * Price growth and promotion growth has a positive impact on sales growth volatility.	✗	x	✓	✗	✓	✗
This study	What is the impact of new product entry at a retailer on own and competing brand sales volatility, and does the new product induced volatility, in turn, affect brand sales?	Retailer new product entry	Own and competing brand sales and sales volatility	*A new product addition to the retailer assortment increase sales volatility for both the innovating and competing brands. * New product, brand, and retailer drivers explain the difference in volatility rise. * New product-induced volatility has a positive impact on the brand's underlying sales levels.	✓	✓	✓	✓	✓	✓

Note: This review includes marketing studies on brand sales volatility following a marketing intervention. NPI = New Product Introduction; IV = independent variable; DV = dependent variable.

Moreover, we are interested if volatility induced by new products will further influence brand sales levels at the retailer *over and above* its direct effect on mean sales levels for the innovating brand. Finally, we assess if (and how) the volatility changes vary across innovations, brands, and retailers. These relations are the basis of our study.

2.3.1 Link between NPI and brand sales volatility at the retailer

In mature CPG categories, consumers tend to have stable preferences and mostly engage in habitual, repeat purchasing whereby consumers choose products that they have purchased in the past (Dubé, Hirsch, and Rossi 2000). This form of consumer inertia in brand choice contributes to stable aggregate sales patterns over time. However, the entrance of a new product can shift consumer's preferences significantly and permanently (van Heerde, Mela, and Manchanda 2004), and is expected to contribute to higher sales volatility for the innovating brand as well as the competing offerings for several reasons. First, a new offering can satisfy new or unmet consumer needs, and there is a high degree of uncertainty in consumers' beliefs and attitudes regarding the innovation's quality and benefits upon entry (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017). But at the same time, it has the potential also to change perceptions of established products through the well-known context effects (Geyskens, Gielens, and Gijsbrechts 2010). These preference changes will be reinforced if sales volatility leads to stock-outs at the retailer that forces consumers to switch brands in-store or postpone their purchases (Campo, Gijsbrechts, and Nisol 2003). Hence, initial stable brand preferences will be disrupted by the entry of a new product, and consumers' brand switching tendencies increase, resulting in less habitual buying. If many consumers try out a new brand at the same time, more volatile aggregate sales patterns across all brands in the category will emerge. Indeed, a product launch has the ability to create 'structural change' and to move brand performance more drastically as it offers strong motivation for consumers to revisit habitual buying patterns and to alternate between the offerings in the same category (van Heerde, Mela, and Machanda 2004; Pauwels and Hanssens 2007).

Second, a new product launch is often accompanied by heavy marketing, both at the market level through advertising pulsing and in-store using promotions or displays, in-store signage, and other merchandising support (Lamey et al. 2018). Such intense marketing is responsible for 'spending bursts' (Chapman and Steenburgh 2011) that induce temporary sales lifts for a brand alternated by offsetting sales drops due to consumer stockpiling behaviour (Ailawadi et al. 2007). Similarly, innovations can be responsible for accelerated revenues due to a sudden sales take-off seeded by positive word-of-mouth and the bandwagon effect that exacerbates sales fluctuations after launch (Goldenberg, Libai, and Muller 2010). This will boost sales for the innovating brand, contributing to more volatile sales patterns for its mother but also for competing offerings when shoppers accustom to buying alternative brands.

Third, also the competitive reactions to NPI further increase volatility in brand sales (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017; Tuli, Bharadwaj, and Kohli 2010). Intense competition through various marketing actions and reactions upon entry will make competing brand sales more volatile as shoppers will concentrate their purchases in the category during promotion weeks, while they refrain from buying the brand at other times due to stockpiling. Again, this chain of marketing actions and reactions among competitors results in more marketing spending by brands and heavy switching between brands around a product launch, contributing to higher volatility in brand sales at the retailer. Therefore, we propose that *new product entry increases volatility not only in own-brand sales but also in competing brands' sales at the retailer*.

2.3.2 Link between (NPI induced) sales volatility and brand sales performance

Arguments for both a negative and a positive relationship between sales volatility and sales (mean) levels can be advanced in the context of NPIs. More volatile sales can inhibit brand success and result in *lower* sales levels in the long run if they damage brand loyalty and prevent building brand relationships. Frequent booms and busts in brand sales could pressure managers to focus too much on pushing consumers to purchase their brands quickly, and they emphasize attractive deals that generate immediate response to gain (or regain) the buyers they lost to competitors. But such practices are known to deteriorate brand loyalty and likely come at the expense of other more valuable brand-building activities aimed at establishing or strengthening a long-term relationship with customers, which benefits a brand in the long run (Ailawadi, Lehmann, and Neslin 2003). Indeed, intense brand switching is problematic for manufacturers to identify consumer needs and to build a strong customer base (Morgan and Rego 2006). In this context, higher sales uncertainty has been found to discourage firms from investing in their brands, making consumers also more hesitant to buy (Minton and Schrand 1999). With more stable purchases, in contrast, it becomes easier to learn about consumer preferences and to adjust brands and adapt marketing support according to their needs (Rao and Bharadwaj 2008). Furthermore, with more uncertainty in brand sales, manufacturers risk that retailers reduce shelf space or delist their offering entirely due to occasional low turnover rates, which will hurt brand sales permanently (Davies 1994). But also, stock-outs at the retailer during frequent sales peaks are detrimental. Research by Campo, Gijsbrechts, and Nisol (2003) shows that consumers predominantly react to stock-outs by switching brands within the store or cancel their purchase altogether, leading to permanent losses for the brand in both instances. This could be especially problematic for innovative products as it may slow down consumer acceptance and result in poor performance. In this context, research on product diffusion also affirms that (technology) innovations with more volatile sales have considerably slower adoption rates (Ferraro 2017). Based on these arguments, we propose that *higher volatility in brand sales after an NPI will have a negative effect on brand mean sales levels and contribute to lower brand performance*.

Arguments in the opposite direction also exist. Building on research in entrepreneurship by DiGregorio (2005) or Hmieleski and Baron (2008), among others, volatility in sales can foster future brand performance when managers exploit the opportunities of high sales peaks, rather than preventing losses of deep sales troughs. Similar opportunities arise for marketers during brand sales peaks after launch. First, during a sales boom, consumers in CPG often stock-up (part of) these purchases at home for future consumption. This stockpiling behaviour has been related to (i) several performance benefits, such as increased consumption and consumption acceleration, (ii) preemptive brand switches (i.e., it preempts consumer's purchase of a competing brand now and in the future), and (iii) a positive impact on repeat purchases (Ailawadi et al. 2007; Neslin and Stone 1996). Indeed, with larger home inventories, consumers will use the brand more and/or more often before their next purchase, leading to a (more) favorable attitude or appreciation of it. This, in turn, increases consumers' likelihood to repurchase it, and they develop higher loyalty towards the brand afterwards, yielding more repeat purchases. This purchase reinforcement mechanism following consumer stockpiling behaviour has also been documented in Dekimpe and Hanssens (1995). Second, during large sales peaks, new consumers likely enter the market and are attracted by the new offering or by one of the established offerings that provide attractive deals. This will generate higher brand knowledge, and more consumers will familiarize themselves with the brands and category early on. Apart from a larger category demand initially, more of these 'trial' buyers that enter the market can be converted into repeat buyers, and product adoption will speed up. This way, sales peaks induced by an NPI may change and shape consumer preferences, resulting in less habitual buying and an interesting window of opportunity to permanently grow the brand's customer base and receive more shelf space (Pauwels and Hanssens 2007). Finally, with irregular and volatile sales patterns, competitive reactions are quite common in an attempt to regain lost buyers. Such intense competition may drive down prices, which again contributes to a beneficial primary demand effect (van Heerde, Mela, and Manchanda 2004). At the same time, sales volatility can act as an entry barrier to prevent more competitors from stepping into the market, which benefits the established offerings (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017). Building on these arguments, we propose that *higher volatility in brand sales after an NPI has a positive effect on brand mean sales levels and contributes to higher brand performance*. Given that two opposing propositions emerge from our discussion, we leave the link between NPI-induced sales volatility and brand sales mean performance as an empirical question.

2.3.3 Drivers of innovation-induced volatility in brand sales

Not all brands experience a sizable change in sales volatility when a new product enters. To understand what drives these differences, we link the change in the innovation-induced volatility across brands and retailers to a set of drivers. Apart from the characteristics of the innovation, we also consider brand factors and the retail environment in which the innovation is offered. The *innovation drivers* relate to the role of innovation type and its success in the market. Most innovations in the CPG market are introduced under an existing brand name, although also genuine new brands occasionally enter the CPG market. We expect own brand innovations to have a larger impact on brand sales volatility compared to innovations launched by competing brands. It is unclear, however, if own brand innovations have a larger impact on sales volatility compared to the entry of an entirely new brand where consumers have no prior information on new brand quality or performance (Balachander and Ghose 2003; Lei, Dawr, and Lemmink 2008). Successful innovations receive more attention from both consumers and competitors compared to less successful ones and have a bigger potential to stimulate brand switching and breach routine brand choices. Hence, we expect a more positive impact on sales volatility for successful innovations than less successful offerings that enter the market.

Also, the *brand* underlying the innovation is expected to drive volatility changes through its market power and positioning and its experience in launching innovations. For example, a brand that ranks high in the market or that is priced at a premium should experience fewer sales turbulence following an NPI, as these brands are valued and appreciated by a steady group of loyal consumers who are less likely to switch to new offerings. In contrast, brands that frequently launch new products build a reputation for being innovative, and consumers have more confidence in their innovations. This will foster innovation trial and encourage switching compared to less innovative brands where consumers face a larger risk to try out the product in the first place.

Finally, a set of *retailer drivers* related to the level of competition and differentiation in the assortment as well as the promotion intensity by the retailer likely influence in-store brand switching tendencies when an innovation enters. Branded new products that enter a retailer where private labels dominate are clearly differentiated from the set of existing assortment offerings and may cater to unmet customer tastes and fit new consumption occasions of its shoppers (Dhar, Hoch, and Kumar 2001). We thus expect a higher level of brand switching when innovations appear in a strong-private label context. Moreover, consumers may be less loyal to individual brands in a store with more frequent promotions and with a larger assortment size consisting of diverse (sub)brands to cater to their customers' heterogeneous needs and/or variety seeking tendency (Bell, Chiang, and Padmanabhan 1999; Vakratsas 2008). The entry of a new product will exacerbate these brand switching tendencies as they provide a reason again to consumers to revisit their choices. Lower brand loyalty and more brand substitution in larger assortments after launch would manifest in more volatile brand sales when a new product enters.

2.4 Data

Setting and data source. We acquired German household panel data from GfK across nine frequently purchased CPG categories: bath & shower gel, biscuits, cola, coffee, crisps, diapers, razors, tea, and yoghurt. The data was available from January 2005 to December 2012 for purchases made at six major German retail chains.[6] During our data period, all six retailers were active in the national market. The retailers are heterogeneous in terms of their business model with two hypermarkets (i.e., a combination of supermarket and department store), two retailers that mostly operate with the supermarket format, and two exemplar hard discounters.

Innovation identification. In each category, we first identified whether an entirely new brand entered the market between January 2006 and December 2010. For this, we used the 12-month initialization period before January 2006 to determine what brands in the 2006-2010 period were not already available for sale in Germany in 2005. On the other end of the data, the 24-month period after December 2010 assures we have enough observations to study

[6] An NDA prohibited us from disclosing the names of the retailers. We refer to them as Retailer 1 to 6 instead.

the performance and volatility in the post-launch period for all NPIs and brands. Across all nine categories, only 11 new brands were launched in the German market, with three categories that had no new brands at all (biscuits, chips, and tea) and up to four new brands entered the diapers category between 2006 and 2010. As the majority of new products in CPG are still launched under an existing and often well-established mother brand name, we further screened the top five manufacturer brands in each category (in terms of their (value) sales across the six retailers over the years 2005-2006). For this set of five top brands x nine categories, all new sub-brands launched in the market between 2006 and 2010 are identified using the same procedure as for the new brands. Table 2.2 summarizes all new products launched in the German market across our categories between January 2006 and December 2010: in total, 182 new products are identified, consisting of 171 sub-brands introduced by 45 established manufacturer brands and 11 new brands.

Table 2.2 Branded Innovations by Category in Germany (2006-2010)

Category	Total No. of New Products	New Sub-Bands	New Brands
Bath & Shower	15	13	2
Biscuit	27	27	0
Coffee	27	25	2
Colas	3	2	1
Crisps	21	21	0
Diapers	15	11	4
Razor	20	19	1
Tea	30	30	0
Yoghurt	24	23	1
Total	**182**	**171**	**11**

Time series. To study brand sales volatility at the retailer, household purchase data were aggregated to the weekly level for each brand at a given retailer and time series by retailer-brand-week over the 417-week time period are obtained starting from January 2nd, 2005 to December 29th, 2012. In each retailer, we evaluated the five leading national brands as well as the retailer's own PL, resulting in 324 (=6 brands x 6 retailers x 9 categories) potential combinations for further analysis. However, not all brands were sold in every retailer (not surprisingly, especially hard discounters carry few of the top 5 brands in their assortment), and we drop combinations where the new brand or sub-brand product was not added by the retailer. Finally, we exclude combinations with less than 50 time series observations from the analysis.[7] As a result, only 214 brand-retailer combinations are retained

[7] Our 50-week cut-off is driven by model convergence considerations. With more missing values, model estimation turned out problematic in many instances (especially when we checked for longer lag lengths in the models).

for further analysis. Sales and price time series are generated for each combination. Weekly value and volume sales are obtained by summing all household spending and volume sold of that brand at the retailer in a week. Similarly, prices are obtained by dividing value by volume sales, so they are expressed per volume equivalent (e.g., €/litres or €/grams) to make offerings with varying package sizes comparable. We deflate all prices using the monthly Consumer Price Index from the Worldbank with reference year 2010.

Drivers of sales volatility. From our screening, we identify whether a new product is launched by an established brand or not. We further derive the brand ranking, its price level, and brand overall innovativeness using data one year prior to the introduction of the focal new product in order to avoid endogeneity concerns, except for the 11 new brands for which no data prior brand data was available. Their brand variables are measured in the year after market entry. Similarly, all retailer drivers are measured one year prior to launch. Finally, we control for differences between discounters and traditional retailers, between food and non-food categories, and whether the incumbent brand is a private label or not. All drivers together with their description and summary statistics are presented in Table 2.3.

2.5 Model-Free Insights

We use the example cola category to provide first insights into the impact of new product entry on brand sales volatility. The cola category faced three NPIs during the data period that were adopted by almost all retailers[8]: Coca Cola Zero (launched in Germany in July 2006) and Coke Light Plus (March 2008) introduced worldwide by the Coca Cola Company to target the increasingly health-conscious customers, and Red Bull Cola, a genuine new brand entering the cola market in Germany in July 2008.

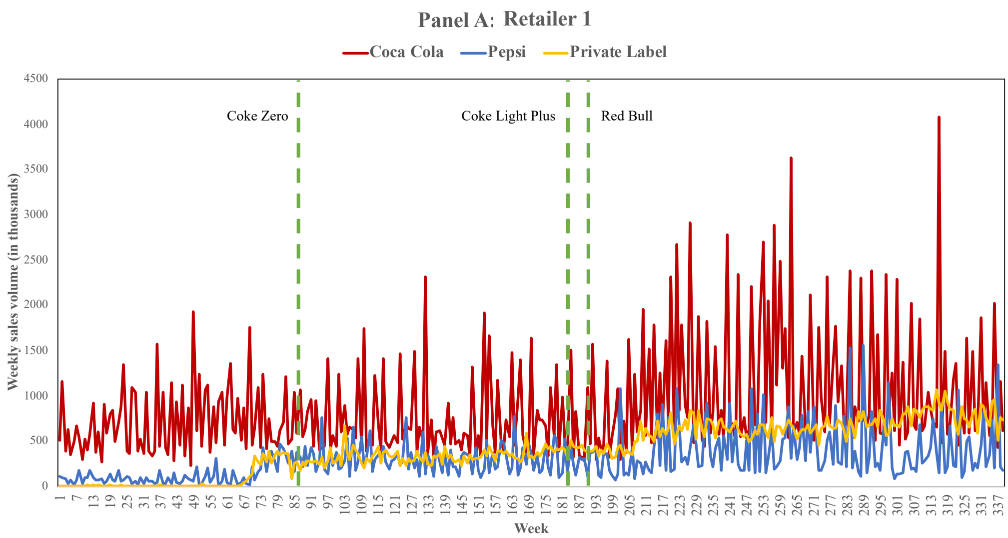
In Figure 2.1, volume sales of Coca Cola, Pepsi, and the retailer's private label are plotted at three example retailers (two mainstream retailers and a hard discounter) from the beginning of the data period until three years after the last introduction at the retailer. The dashed vertical lines in Figure 2.1 indicate the retailer's innovation adoption time of each new product (note that Red Bull cola was not adopted by Retailer 3). Especially the Coke Zero innovation turned out successful both from a brand and retailer perspective, as evidenced by the rise in regular Coke sales after launch in all three retailers. But we are more interested in the sales volatility after product launch. As expected, the introduction of all three innovations

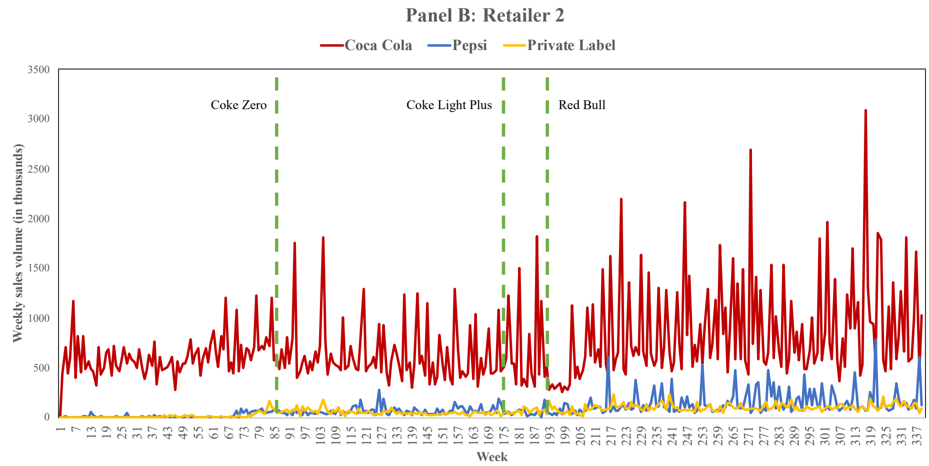
[8] Aldi did not offer any of the new products in cola category during the data period and hence, dropped out of the cola analysis. In Lidl, the new Red Bull cola brand was not available, but the two other Coca Cola innovations were offered. Hence, the cola analysis involves five out of the six retailers in our dataset.

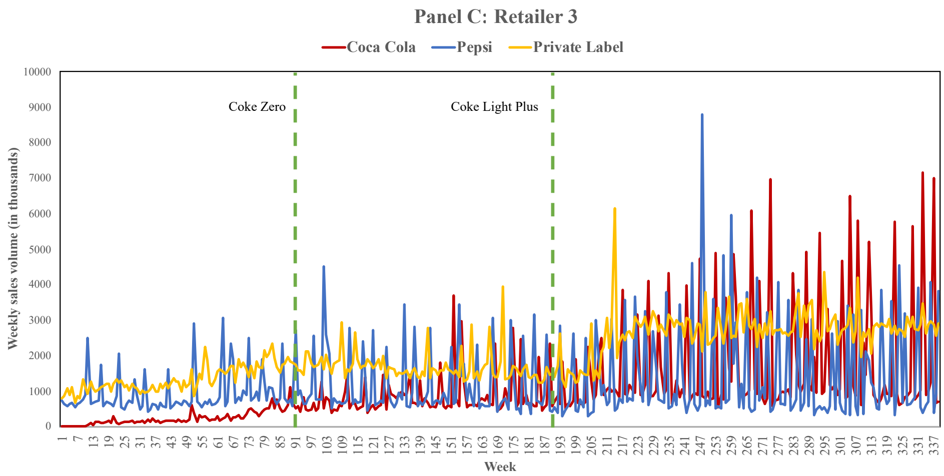
led to a period of instability in brand sales at the retailers, generating a series of effects on the Coca Cola brand and its main competing brands Pepsi and the retailer's private label. Volatilities in sales of all brands clearly increased and became more intertwined once innovation was adopted by the retailer. The increase in sales volatility of Pepsi and the private label suggests more consumer brand switching and unstable sales patterns also for competing brands after launch.

Figure 2.2 visualizes the link between mean sales and sales volatility of the Coca Cola brand by retailer over time. For this, we divided our data period into 20 intervals with equal lengths (20 weeks each for the first 19 intervals and 17 weeks for the last interval) and calculated the mean and standard deviation of sales during each time interval. The solid line refers to mean sales levels, and the dashed line refers to volatility (i.e., the standard deviation in sales over that interval). As before, the vertical line is the adoption time of each innovation by the retailer. From these graphs, it can be seen that mean sales and sales volatility in general co-move in all retailers, and hence, periods of higher sales volatility are associated with increased (not lower) sales levels.

Figure 2.1 Weekly Volume Sales of Coca Cola, Pepsi Cola, and Retailer's Private Label by Retailer

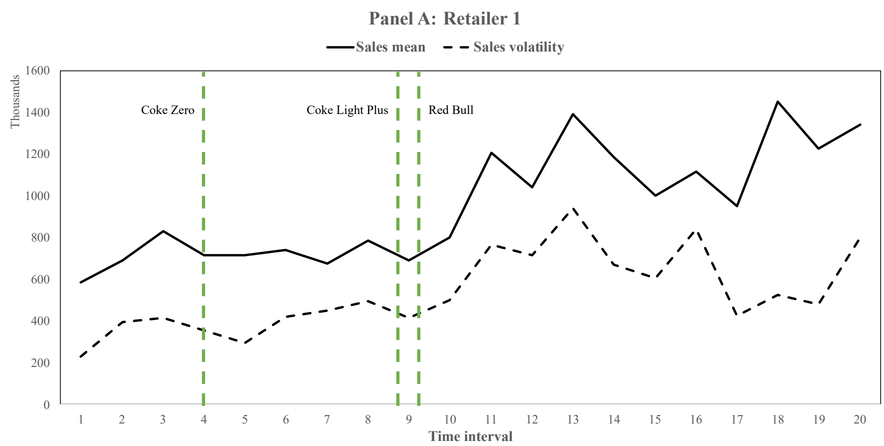


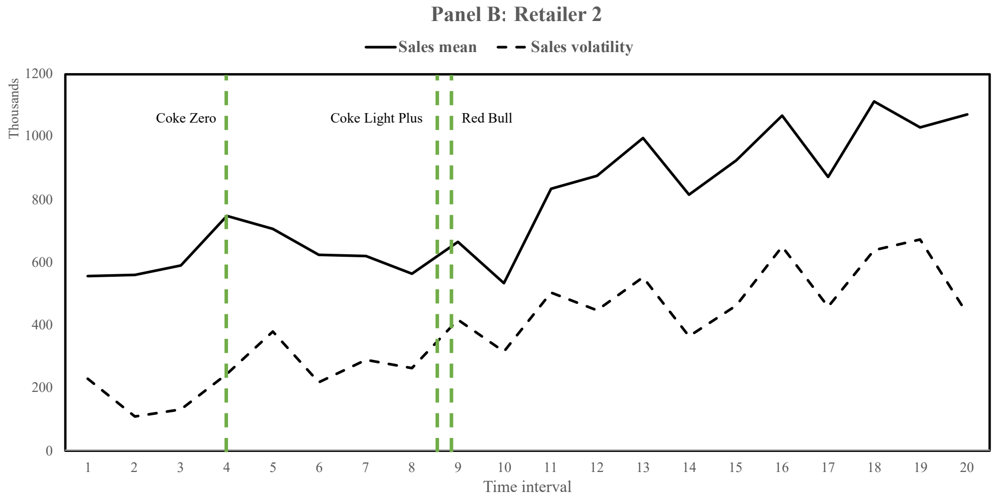


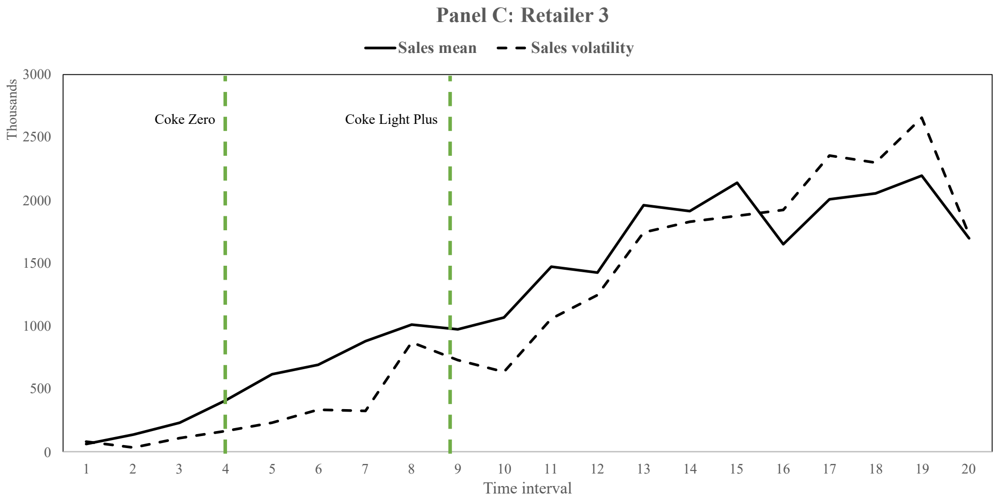


Note: The plots cover the entire period before the introduction of the first innovation (Coke Zero) and three years after the last new product was adopted by the retailer. The vertical dashed lines in green refer to the adoption time of each new product by the respective retailer.

Figure 2.2 Coca Cola Brand Level Mean Sales and Volatility over 20 Time Intervals







Note: Each time interval consists of 20 weeks except the 20th interval that includes 17 weeks. Sales volatility is measured as the Standard Deviation (SD) during the respective sub-period or interval. The vertical dashed lines in green refer to the adoption time of each new product by the respective retailer.

2.6 Method

Our modelling approach consists of two stages. In the *first stage*, we use a Volatility-in-VAR to assess the impact of new product entry on sales volatility and the subsequent volatility-sales relationship over time. In the *second stage*, the estimates from the first stage analysis that capture the over-time volatility changes across our brands and retailers are further linked to a set of moderators in a cross-sectional Weighted Least Squares (WLS) model to explain what drives the changes in sales volatility across new products, brands, and retailers. Table 2.4 outlines our modelling approach and the corresponding steps.

Table 2.3 Variables and their Measurement in the Second Stage Regression

Variables	Measurement	Mean[a]	s.d.	Min	Max
New product variables					
New brands *dNEWBRDb*	Dummy = 1 for the introduction of an entirely new brand in the category of brand *b*, 0 else	17.15%	0.377	0	1
Competing new product *dCOMNPb*	Dummy = 1 for the introduction of a new product by a (top 5) competitor of brand *b*, 0 else	25.30%	0.435	0	1
New product success *INVSUCpb*	National (volume) share of new product *p* in the category of brand *b* in its first year after market launch	0.007	0.012	0	0.090
Brand variables					
Brand rank *BRDRANKb*	National rank of brand *b* in the category in terms of total sales value	3.305	1.630	1	8
Brand price premium *BRDPREMb*	Price difference expressed as a ratio of the price of brand *b* to the (retailer weighted) private-label price in the category	1.760	1.343	0.272	7.953
Brand innovativeness *BRDINVb*	Cumulative number of innovations launched in the market by brand *b* over the full data period	4.746	3.087	0	11
Retailer variables					
Retailer concentration *RETCONCbr*	Sum of the share of the 5 largest brands within each retailer *r* in the category of brand *b*	0.242	0.172	0	0.886
Retailer price volatility *RETPROMbr*	Promotion intensity measured through the Coefficient of Variation in prices of the top 5 brands in the category of brand *b* at retailer *r*	9.522	34.803	0.016	173
Retailer assortment size *RETASSORbr*	Ln-transformed total number of sub-brands offered at retailer *r* in the category of brand *b*	57.207	98.710	1	479
Retailer PL salience *RETPLbr*	(Volume) share of private-label brands in the category of brand *b* at retailer *r*	0.413	0.378	0.004	1
Control variables					
Discounter retailer *dDISCr*	Dummy = 1 if retailer r is a discounter, 0 else	10.22%	0.303	0	1
Food category type *dFOODb*	Dummy = 1 if the category of brand b is a food category, 0 else	74.60%	0.436	0	1

[a] Statistics are reported before weighting and ln-transformation. For dummy variables, we report the percentage of observations having the value of one. Note: Unless otherwise specified, innovation-level drivers are measured in the year after innovation launch while brand- and retailer-level drivers are measured in the year prior to innovation launch.

Table 2.4 Summary of the Modelling Approach

Stage	Step	Modelled Item	Model Adopted	Model Purpose
1. Volatility modelling (over time)	1	weekly sales level	VAR	NPI → sales level
	2	weekly sales volatility	MGARCH	NPI → sales volatility
	3	weekly volatility-in-mean	Volatility-in-VAR	NPI → sales volatility → sales level
2. Moderators of volatility (cross-sectional)		change in sales volatility across NPIs, brands and retailers	Weighted Least Square regression	Drivers → NPI-induced volatility

Notes: VAR = Vector Autoregressive model. MGARCH = Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model. Step 2 and 3 in stage 1 are repeated until the difference in log-likelihood between successive models becomes very small to ensure estimation efficiency.

Stage 1: Modelling sales volatility in relation to new product entry

Volatility cannot be observed directly, but it represents the fluctuations in a series around its expected value or 'conditional mean' (Franses and van Dijk 1996). Accordingly, this requires a model that first determines the expected value of the brand sales series Y *conditional* on the factors X that drive overtime changes in Y, after which the volatility can be determined. The changes in sales volatility are linked to market events associated with, among others, new product entry, and we further assess if a rise or drop in volatility also drives subsequent mean sales levels.

To model this formally, for each brand-retailer combination, we proceed in three steps. In s*tep 1*, we simultaneously estimate the conditional mean and volatility using a standard Vector Autoregressive (VAR) model and a multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model extended with product entry variables in each equation. Using the estimated parameters from the GARCH equation, in *step 2,* we compute the predicted conditional volatilities. In *step 3*, we incorporate these computed conditional volatilities back into the VAR model and estimate the *Volatility-in-VAR* model. To improve the model efficiency, we repeat this loop until the likelihoods of the consecutive models are very close to each other.

STEP 1: Conditional mean and volatility modelling.

We jointly model the series mean level and volatility with a VAR and Constant Conditional Correlation (CCC)-GARCH model (Bollerslev 1990), where the impact of new products is modelled explicitly through a set of exogenous variables associated with product entry. Equations 1 and 2 show the VAR model formulation that captures the dynamic interactions between brand sales and price variables. In this VAR, the conditional mean in brand (volume) sales and the price at the retailer are a function of their own past, new product introductions, and a number of standard control variables. Note that due to the scaling of our sales variable (with large numbers), mean–centering the sales series was required to reach model convergence in our estimations. Details on all variables in the models and their measurement are provided in Table 2.5.

$$\begin{bmatrix} Sales_t \\ Price_t \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \end{bmatrix} + \sum_{i=1}^{I} \begin{bmatrix} \alpha_{11}^{i} & \alpha_{12}^{i} \\ \alpha_{21}^{i} & \alpha_{22}^{i} \end{bmatrix} \begin{bmatrix} Sales_{t-i} \\ Price_{t-i} \end{bmatrix} + \begin{bmatrix} \beta_{11} \dots \beta_{1n} \\ \beta_{21} \dots \beta_{2n} \end{bmatrix} \begin{bmatrix} dNP\_ENTRY1_t \\ \dots \\ dNP\_ENTRYn_t \end{bmatrix} +$$

$$\begin{bmatrix} \beta_{31} \dots \beta_{3m} \\ \beta_{41} \dots \beta_{4m} \end{bmatrix} \begin{bmatrix} dBR\_ENTRY1_t \\ \dots \\ dBR\_ENTRYm_t \end{bmatrix} + \begin{bmatrix} \beta_5 \\ \beta_6 \end{bmatrix} [CNP\_ENTRY_t] + \Gamma . Z_t + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (2.1)$$

where *t* denotes the time index for week, *i* stands for the number of lags used for the sales and price variables, index *n* and *m* represent the number of own brand new product entries and entire new brands, respectively, and Z is a matrix with the controls. In Eq.2.1, we separate the effect of (1) own-brand introductions, (2) the introduction of entirely new brands in the category, and (3) new product introductions by competing brands on brand sales and prices. While we use separate dummies to capture the effect of each own brand's new product introduced at the retailer and each new brand that enters the category, we combine the effect of new products launched by competing brands. This is done with a count variable that starts with a value 0 in the first week, and in each week where one of the competing national brands launched an innovation, we add a value of one.[9] We further specify the controls in Z_t in Eq. 2.2:

[9] Our introduction dummies take the form of a step dummy, and hence, capture the long-term rise in sales and/or volatility after NPI. Although we do not allow for it explicitly, the VAR and GARCH models accounts for a potential 'transition' (or dust-settling) period immediately after launch. Based on the preliminary unit root test (see Results section), our series turn out mean reverting. For such series, the lagged endogenous variables in the VAR and GARCH models allow for any temporary deviation from the long-term stable pattern in the series to revert to the new equilibrium level and thus, for the impact of exceptional temporary sales or volatility spikes around NPI to slowly die out.

$$Z_t = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} \end{bmatrix} \begin{bmatrix} CPRI_t \\ PLPRI_t \\ dFPRO_t \\ CPRO_t \\ dPLPRO_t \end{bmatrix} + \begin{bmatrix} \delta_{11} \\ \delta_{21} \end{bmatrix} [R\_ASSI_t] + \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} \begin{bmatrix} SEAS1_t \\ SEAS2_t \end{bmatrix} \quad (2.2)$$

These controls account for the impact of changes in regular prices of the main competing brands as well as the retailer's own private label at the store (*CPRI* and *PLPRI*), the impact of price promotions at the store by the focal brand (*dFPRO*), competing national brands (*dCPRO*), and the retailer's private label. Retailers also regularly add and remove offerings, so the model further controls for changes in assortment size over time (*R_ASSI*). Finally, in line with Gielens (2012), two trigonometric seasonal terms are added to account in a parsimonious way for seasonal fluctuations in brand sales and prices. More details are provided in Table 4. The error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ in Eq. 1 are normally distributed with zero mean and a time-varying (heteroscedastic) variance: $\varepsilon_{1,t} \sim N(0, h_{1,t})$ and $\varepsilon_{1,t} \sim N(0, h_{2,t})$. Let us denote the conditional covariance matrix of these residuals by H_t. In MGARCH models, H_t is decomposed into conditional standard deviations (i.e., volatility) and correlations. In matrix form, it is expressed as:

$$H_t = D_t^{1/2}\, S\, D_t^{1/2},$$

where *S* is the time-invariant conditional correlation matrix:

$$S = \begin{bmatrix} 1 & s_{12} \\ s_{12} & 1 \end{bmatrix},$$

and D_t is the diagonal matrix with conditional variances:

$$D_t = \begin{bmatrix} h_{1,t} & 0 \\ 0 & h_{2,t} \end{bmatrix}.$$

Each element in D_t evolves according to the following GARCH process:

$$h_{1,t} = \sum_{j=1}^{J} \phi_{1,j}\, \varepsilon_{1,t-j}^2 + \sum_{k=1}^{K} \psi_{1,k}\, h_{1,t-k} + \exp(\tau_{11} + \sum_{n=1}^{N} \tau_{12n}\, dNP\_ENTRYn_t + \sum_{m=1}^{M} \tau_{13m}\, dBR\_ENTRYm_t + \tau_{14}\, CNP\_ENTRY_t + \mathrm{T}_1.Z_t) + v_{1,t} \quad (2.3a)$$

$$h_{2,t} = \sum_{j=1}^{J} \phi_{2,j}\, \varepsilon_{2,t-j}^2 + \sum_{k=1}^{K} \psi_{2,k}\, h_{2,t-k} + \exp(\tau_{21} + \sum_{n=1}^{N} \tau_{22n}\, dNP\_ENTRYn_t + \sum_{m=1}^{M} \tau_{23m}\, dBR\_ENTRYm_t + \tau_{24}\, CNP\_ENTRY_t + \mathrm{T}_2.Z_t) + v_{2,t} \quad (2.3b)$$

with $v_{1,t}$ and $v_{2,t}$ the normally distributed error terms with zero mean and a constant variance. By adding the volatility dynamics acquired from the GARCH into the VAR model, we can simultaneously model the mean levels and volatility in a series and let both vary as a function of new product entry. In fact, the estimates τ_{121} to τ_{14} capture the impact of new product entry on brand sales volatility. To further assess if this new product induced volatility changes subsequent brand sales level, we proceed with steps 2 and 3, where the conditional volatility estimates are incorporated back into the VAR model.

STEP 2: Compute the predicted volatilities.

In step 2, we compute the predicted volatilities over time using the estimated parameters from the Eqs. 2.1 to 2.3 in step 1:

$$\hat{h}_{1,t} = \sum_{j=1}^{J} \hat{\phi}_{1,j}\, \hat{\varepsilon}_{1,t-j}^{2} + \sum_{k=1}^{K} \hat{\psi}_{1,k}\, \hat{h}_{1,t-k} + \exp\,(\hat{\tau}_{11} + \sum_{n=1}^{N} \hat{\tau}_{12n}\, dNP\_ENTRYn_t + \sum_{m=1}^{M} \hat{\tau}_{13m}\, dBR\_ENTRYm_t + \hat{\tau}_{14}\, CNP\_ENTRY_t + \hat{\mathrm{T}}_1 . Z_t) \quad (2.4a)$$

$$\hat{h}_{2,t} = \sum_{j=1}^{J} \hat{\phi}_{2,j}\, \hat{\varepsilon}_{2,t-j}^{2} + \sum_{k=1}^{K} \hat{\psi}_{2,k}\, \hat{h}_{2,t-k} + \exp\,(\hat{\tau}_{21} + \sum_{n=1}^{N} \hat{\tau}_{22n}\, dNP\_ENTRYn_t + \sum_{m=1}^{M} \hat{\tau}_{23m}\, dBR\_ENTRYm_t + \hat{\tau}_{24}\, CNP\_ENTRY_t + \widehat{\mathrm{T}_2} . Z_t) \quad (2.4b)$$

Thus, by taking the square root of $\hat{h}_{1,t}$ and $\hat{h}_{2,t}$, we obtain the predicted sales and price volatilities in week t, irrespective of their source.

STEP 3: Volatility-in-VAR model.

To further examine if the sales volatility endogenously affects the future sales levels, in step 3, we incorporate the predicted volatilities from step 2 back into the VAR model and estimate it jointly with the volatility model. Note that we include the *lagged* predicted volatility estimates rather than their instantaneous effect to avoid reverse causality concerns in which higher (lower) mean levels cause higher (lower) volatility in the series[10]:

$$\begin{bmatrix} Sales_t \\ Price_t \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \end{bmatrix} + \sum_{i=1}^{I} \begin{bmatrix} \alpha_{11}^{i} & \alpha_{12}^{i} \\ \alpha_{21}^{i} & \alpha_{22}^{i} \end{bmatrix} \begin{bmatrix} Sales_{t-i} \\ Price_{t-i} \end{bmatrix} + \begin{bmatrix} \beta_{11} \dots \beta_{1n} \\ \beta_{21} \dots \beta_{2n} \end{bmatrix} \begin{bmatrix} dNP\_ENTRY1_t \\ \dots \\ dNP\_ENTRYn_t \end{bmatrix} + \begin{bmatrix} \beta_{31} \dots \beta_{3m} \\ \beta_{41} \dots \beta_{4m} \end{bmatrix} \begin{bmatrix} dBR\_ENTRY1_t \\ \dots \\ dBR\_ENTRYm_t \end{bmatrix} + \begin{bmatrix} \beta_5 \\ \beta_6 \end{bmatrix} [CNP\_ENTRY_t] + \Gamma . Z_t + \begin{bmatrix} \zeta_{11} & \zeta_{12} \\ \zeta_{21} & \zeta_{22} \end{bmatrix} \begin{bmatrix} \sqrt{\hat{h}_{1,t-1}} \\ \sqrt{\hat{h}_{2,t-1}} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \qquad (2.5)$$

[10] The temporal precedence where a series lagged value in period *t-1* is related to another series value in period *t* in a relationship to empirically establish a causal relationship is in line with the Granger causality idea (see also Srinivasan, Rutz, and Pauwels 2016 for a marketing application). Similar findings, however, occur if we include in Eq. 5 the instantaneous volatility estimates instead of the one period lag.

Table 2.5 Variables and their Measurement in the Brand VAR and GARCH Models

Brand sales *$Sales_t$*	(Mean-centred) total brand sales volume at the retailer in week *t*.
Brand price *$Price_t$*	The average (deflated) regular price of the brand at the retailer in week *t* (average price used in promotion weeks).
Focal brand entry *dNP_ENTRYn_t*	Step dummy taking the value = 1 in the weeks after new product n by the focal brand enters the retailer, and value 0 before entry.
New brand *dBR_ENTRYm_t*	Step dummy taking the value = 1 in the weeks after a completely new brand m enters the retailer, and value 0 before entry.
Competing brand entry *CNP_ENTRY_t*	Count variable starting from 0 in week 1 and increasing with 1 in each week *t* when a new product by one of the competing TOP 5 brands available from the retailer enters the assortment.
Competing brand price *$CPRI_t$*	Weighted average (deflated) regular price (in volume equivalents) of the other top five competing brands available at the retailer in week *t* (average price used in promotion weeks). Static weights are used to construct the weighted competitive price variables, with the average brand market share (in terms of sales) over the entire data period as the weight.
Private label price *$PLPRI_t$*	Average (deflated) regular price (in volume equivalents) of the private label at the retailer in week *t* (average price used in promotion weeks). In case there are more private labels available at the retailer, we take a weighted price with the average retail share in the respective year as a weight.
Focal brand promotion *$dFPRO_t$*	Promotion dummy = 1 if actual price of the focal brand in week *t* shows a negative shock of at least 1 standard deviation below the brand's average (non-promoted) price at that retailer, 0 else
Competing brand promotion *$CPRO_t$*	The number of competing top 5 brands available from the retailer that is offered with a promotion in week *t* at the retailer.
Private label promotion *$dPLPRO_t$*	Dummy = 1 if the private label is offered with a promotion in week *t,* 0 else. In case more private labels are available at the retailer, the dummy =1 if *any* of these private labels is on promotion that week.
Assortment size *R_ASSI_t*	Count variable with the number of subbrands offered in the category at the retailer in week *t*
Seasonal variables *$SEASq_t$*	Two trigonometric terms are used to capture seasonal fluctuations (q = 1, 2). The variable is constructed as sin(2πt/52) for q=1, and cos(2πt/52) for q=2 with *t* the corresponding week number.

Notes: Prices for all SKUs belonging to a brand are weighted using as a weight each SKU's volume share in total brand sales at that retailer in that week. In line with Nijs, Srinivasan, and Pauwels (2007), a promotion week for a brand in a retailer is identified when a brand's weekly price is lower than one standard deviation below its average price at that retailer (average price over the entire data period at that retailer).

Model Efficiency.

To ensure the efficiency of the parameters, we repeat the above steps 2 and 3 until the difference in the log-likelihoods of the successive models becomes very small, i.e. $|LL_a - LL_{a+1}| < \epsilon$, where *a* stands for iteration and ϵ is a small number, i.e., 0.1. In Eq. 2.5, a significant and positive (negative) estimate ζ_{11} is indicative of a positive (negative) effect of brand sales volatility on subsequent mean sales levels, while the relation is absent if the estimate is insignificant.

Stage 2: Explaining what drives changes in sales volatility following new product entry

Once the models in stage 1 are estimated across our set of brands and retailers, we stack all estimates τ_{12n}, τ_{13m} and τ_{14} and they become the dependent variable in a second stage regression linking the size of the sales volatility change to the innovation, brand and retailer drivers as well as the controls in Eq. 2.6:

$$[\hat{\tau}_{12n,}\hat{\tau}_{13m},\hat{\tau}_{14}]_{br} = c0 + c1.dNEWBRD_b + c2.dCOMNP_b + c3.NPSUCCESS_p + c4.BRDPRI_b + c5.BRDRANK_b + c6.BRDINV_b + c7.RETCONC_{br} + c8.\ RETPROM_{br} + c9.RETASSOR_{br} + c10.\ RETPL_{br} + \ c11.\mathrm{dDISC}_r + \mathrm{c12.dFOOD}_b + u_{pbr}\ , (2.6)$$

with all indices as before and index p = 2, 3, 4 for own new products (p=2), new brands (p=3), and competing new products (p=4) that enter the market, respectively, b the brand index and r an index for the retailer. Details on all independent variables in Eq. 6 and their measurement are provided in Table 2.3. Because the dependent variable contains estimated values characterized by different degrees of estimation precision, OLS may yield bias estimates of the standard errors if the residuals exhibit heteroscedasticity. In that case, we use a WLS estimation approach to estimate Eq. 6 where we weighed all observations by the inverse of the standard error of the estimated dependent variable (acquired from stage 1 models) to offer more weight to observations with more precise estimates (i.e., with lower standard errors) (see Shankar and Krishnamurthi 1996; Kubler et al. 2018).

2.7 Results

2.7.1 Preliminary analysis and model specification

Standard exploratory data analyses are conducted to assess stationarity and to capture the autocorrelation patterns in our series properly. First, to test for stationarity, we rely on the Augmented Dickey-Fuller (ADF) test. For the majority of our 214 series, the null hypothesis that the series contains a unit root could be rejected based on the ADF test ($p < 0.10$; see Table 2.6), and we can proceed with our VAR models in levels. For the 10 series where we do find a unit root, we also implemented the Structural Break Unit Root tests (Perron 1989) that allows for a break in the series in the week of a new product launch. When we allowed for such breaks, no unit roots could be detected in any of the series. Second, the lag order of the endogenous variables should be sufficiently large to ensure that the residuals of the VAR and GARCH are not auto-correlated. To determine the number of lags, we follow a stepwise procedure in which we estimate alternative lag models and use standard information criteria to choose among these models (cf. Dekimpe and Hanssens 1995; Lütkepohl, 1993). In this procedure, we start with a first-order lag VAR model and sequentially increase the lag order with one until the (symmetric lag) VAR model no longer converges. For all models where convergence is reached, we compare model performance based on the Log-likelihood, AIC, and BIC to select the final lag order. Following this procedure, a VAR model with one lag in both equations turns out most appropriate in all instances. For the GARCH model, different lags for prices and sales were required to remove autocorrelation and heteroscedasticity from the residuals. Taking into account the same model convergence issues and procedure, the information criteria suggest that between one lag and four lags is needed to the alternative sales and price GARCH specifications.

Table 2.6 Summary of Model Diagnostics Results

Category	Unit Root Test[a]	Likelihood Ratio Test[b]	ARCH Test[c]
Bath & Shower	26/29	29/29	29/29
Biscuit	20/20	20/20	20/20
Coffee	29/29	27/29	29/29
Colas	23/25	25/25	25/25
Crisps	29/29	29/29	29/29
Diapers	11/14	14/14	14/14
Razor	15/17	17/17	17/17
Tea	26/26	25/26	26/26
Yoghurt	25/25	25/25	25/25
Total	*204/214*	*211/214*	*214/214*

[a] The Augmented Dickey-Fuller (ADF) test with an intercept and trend is used to test for the presence of a unit-root test ($p < 0.10$). If the test statistic indicates a unit root, a subsequent Structure Break Unit Root test that allows for a break at the time of an NPI could reject the presence of a unit root in all instances. [b] Log-likelihood of a VAR model with and without time-varying volatility terms are compared ($p < 0.10$). [c] Based on a Chi-square test for the no conditional heteroscedasticity null hypothesis ($p < 0.10$). Note: No. of significant series/Total no. of series are reported for each category.

Although visual inspection of the example data in Figure 2.1 already suggests that the variance in the sales series is not constant but changes around innovation launch, we also formally checked if the VAR models where we omit the volatility variables in the third step performed significantly worse. Formal Likelihood-ratio tests, however, indicated that the VAR models with varying volatility perform indeed better than without it for 211 out 214 models ($\chi^2(4)$ significant at $p < 0.10$, see Table 2.6). This is also confirmed by the lower AIC for models with varying volatility. Moreover, the Engle's (1982) ARCH tests to test the null hypothesis of no conditional heteroscedasticity (i.e., no autocorrelations in the squared residuals of the VAR) were rejected for all brand-retailer combinations, with test statistics all significant at the 10% level (see Table 2.6).

2.7.2 Model findings example cola category

We first present detailed model estimates for the sales equations in both the VAR and GARCH for the example cola category in Tables 2.7 and 2.8.[11] To capture the introduction of three new products, three NPI dummies are added to the Coca Cola models to capture their respective impact on mean sales and sales volatility (*dZERO, dLIGHTPLUS,* and *dREDBULL*). In models for the other cola brands (i.e., Pepsi, Sina, Vita, and private label[12]), we have one dummy for the Red Bull new brand introduction and capture the competing Coca Cola innovations with a count variable (*CNP_ENTRY*) that measures the cumulative impact of both new products on sales and volatility. The variable *CNP_ENTRY* ranges between 0 and 2 since Coca Cola is the only competing brand that introduced new products in the cola category that period.

The results for the control variables in the Coca Cola models in Table 2.6 are plausible. The estimate of own brand regular price on Coca Cola mean sales, captured by the lagged price variable in the mean sales equations, has the expected negative sign and is significant for all three retailers. The results in Table 2.7 also show that Coca Cola sales is hardly affected by changes in the regular prices of competing national brands, with insignificant effects for CPRI observed across all retailers. However, sales are affected by the regular price of PL brands, with positive and significant results for PLPRI in 2 out of 3 models presented. Own-brand promotion has a dominant positive significant effect suggesting a boost in sales during promotion weeks. Promotions by competing national brands and PL offered by the retailer have a consistently negative impact on cola sales, although not always significant. Finally, retailer assortment proliferation had a significant and negative effect on sales only at Lidl. In the volatility models, own brand promotions clearly boost sales volatility (significant positive impact across all three models), but volatility is unrelated to competing brand prices and promotions. Moreover, also assortment changes (including new product entry) drive brand sales volatility at the retailer.

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[11] Although we jointly model brand sales and price in the VAR and GARCH models as outcome variables, we only report the results of the sales mean and sales volatility equations as these are our main interest. The estimation results for the price equations are available from the authors upon request.

[12] Glorietta, the 5th national brand in cola category, had fewer than 50 observations at each retailer and is therefore omitted.

Table 2.7 Model Results Example Coca Cola Brand at Three Retailers

	Retailer 1		Retailer 2		Retailer 3	
VARIABLES	Mean Sales	Sales Volatility	Mean Sales	Sales Volatility	Mean Sales	Sales Volatility
dZERO	67,145***	0.796***	373,814***	0.305	-72,738*	0.227
	(11,960)	(0.133)	(44,506)	(0.255)	(42,502)	(0.289)
dLIGHTPLUS	13,950	1.574***	425,974***	2.676***	28,512	0.409
	(24,457)	(0.211)	(72,691)	(0.324)	(53,586)	(0.386)
dREDBULL	431,969***	3.299***			204,155	2.349***
	(25,756)	(0.219)			(127,965)	(0.379)
Sales_vol(-1)	0.052*		0.068***		0.150	
	(0.031)		(0.0240)		(0.238)	
Price_vol(-1)	105,231		56,178		325,262	
	(173,079)		(51,645)		(223,279)	
sales(-1)	-0.071***		0.025		0.101**	
	(0.017)		(0.0190)		(0.048)	
price(-1)	-121,083***		-26,853*		-133,014***	
	(27,285)		(17,134)		(31,068)	
CPRI	6,727	0.113	15,665	0.477***	6,820	-0.150
	(16,565)	(0.164)	(19,710)	(0.114)	(20,383)	(0.099)
PLPRI	8,296***	0.031	-301,849	-1.570	24,429*	0.167
	(2,955)	(0.079)	(195,275)	(1.173)	(14,090)	(0.113)
dFPRO	584,970***	1.670***	1.849e+06***	3.690***	363,296***	1.370***
	(16,794)	(0.222)	(228,872)	(0.197)	(57,978)	(0.210)
CPRO	-48,611***	-0.061	-32,002	-0.152	-34,277	-0.248**
	(17,604)	(0.092)	(28,035)	(0.206)	(22,723)	(0.116)
dPLPRO	-36,236	-0.344	-134,530	-0.949	-27,213	-0.704***
	(27,745)	(0.515)	(105,102)	(0.588)	(58,226)	(0.207)
R_ASSI	31,649	-0.551	-496,292**	-9.015***	18,845	-0.090
	(96,468)	(1.113)	(214,740)	(1.351)	(93,008)	(0.513)
arch(-1)		0.007***		0.005		-0.016
		(0.001)		(0.004)		(0.020)
garch(-1)		-0.182***		-0.004**		-0.030
		(0.020)		(0.002)		(0.097)
SEAS1	22,621		-10,133		3,887	
	(18,283)		(18,233)		(16,559)	
SEAS2	10,891		-38,599*		-12,187	
	(7,026)		(22,499)		(18,259)	
Constant	-1.503e+06***	24.68***	343,518	39.92***	-1.525e+06***	24.47***
	(245,921)	(2.502)	(665,717)	(4.295)	(302,142)	(1.101)
Observations	414		414		414	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (p-values 1-sided). *Notes: Standard errors in parentheses. Variable 'salesvol(-1)' corresponds to the estimate related to* $\sqrt{\hat{h}_{1,t-1}}$ *and variable 'pricevol(-1)' contains the estimate for* $\sqrt{\hat{h}_{2,t-1}}$ *in the sales model in Eq. 5.*

Table 2.8 Summary Results All Brand-Retailer Models Cola Category

		Edeka	Kaufland	Lidl	Real	Rewe
Coca Cola	Sales mean salesvol(-1)	0.314***	0.052*	0.068***	0.758***	0.150
		(0.084)	(0.031)	(0.024)	(0.219)	(0.238)
	Sales volatility *dZERO*	0.104	0.796***	0.305	1.264***	0.227
		(0.543)	(0.133)	(0.255)	(0.227)	(0.289)
	Sales volatility *dLIGHTPLUS*	0.028	1.574***	2.676***	0.013	0.409
		(0.106)	(0.211)	(0.324)	(0.169)	(0.386)
	Sales volatility *dREDBULL*	1.334***	3.299***		0.464***	2.349***
		(0.346)	(0.219)		(0.178)	(0.379)
Pepsi	Sales mean salesvol(-1)	0.059	0.072	1.309***	0.102**	0.169***
		(0.055)	(0.075)	(0.12)	(0.043)	(0.064)
	Sales volatility *CNP_ENTRY*	0.487	0.768***		0.348*	0.233***
		(0.499)	(0.197)		(0.193)	(0.087)
	Sales volatility *dREDBULL*	0.332	0.181		1.499***	0.275
		(0.524)	(0.292)		(0.179)	(0.299)
Sina	Sales mean salesvol(-1)	0.126	0.051	0.071	0.377*	0.339
		(0.143)	(0.065)	(0.256)	(0.208)	(0.227)
	Sales volatility *CNP_ENTRY*	1.115***	0.092	1.127***	0.234	0.686***
		(0.265)	(0.232)	(0.419)	(0.149)	(0.213)
	Sales volatility *dREDBULL*	2.194***	0.921**		0.246	0.392
		(0.360)	(0.359)		(0.213)	(0.332)
Vita	Sales mean salesvol(-1)	0.316	0.034	-0.789	0.300**	0.0241
		(0.221)	(0.104)	(1.845)	(0.121)	(0.370)
	Sales volatility *CNP_ENTRY*	0.111	0.291	2.187***	0.314**	0.565
		(0.234)	(0.213)	(0.717)	(0.123)	(0.359)
	Sales volatility *dREDBULL*	0.368	0.432		0.996**	0.362
		(0.134)	(0.348)		(0.402)	(0.373)
PL	Sales mean salesvol(-1)	0.202***	0.499	0.939	0.183	1.353***
		(0.018)	(0.397)	(0.870)	(0.347)	(0.169)
	Sales volatility *CNP_ENTRY*	0.273	0.052	0.928***	0.033	0.348***
		(0.427)	(0.971)	(0.146)	(0.138)	(0.039)
	Sales volatility *dREDBULL*	0.716*	0.886**		0.492**	0.415
		(0.431)	(0.323)		(0.232)	(0.562)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (p-values 1-sided). *Notes: Standard errors in parentheses. Estimates in the mean sales models relate to the lagged sales volatility where 'salesvol(-1)' contains the estimate of* $\sqrt{\hat{h}_{1,t-1}}$ *in Eq. 5. Similarly, the estimates for the sales volatility model refer to the new product introductions by the mother brand (dZERO and dLIGHTPLUS, only for Coca Cola), by competing brands (CNP_ENTRY), and the introduction of the new Red Bull brand (dREDBULL).*

The relation between NPI and sales volatility. With respect to our first research proposition, the results from the cola category in Table 2.7 and 2.8 provide clear and consistent evidence that the entry of innovations significantly raises sales volatility, not just for the innovating brand but also for most of its competitors at the store. From Table 2.7, it is evident that the launch of its two sub-brands, i.e., Coke Zero and Coke Light Plus, and the launch of Red Bull were all responsible for an increase in sales volatility of Coca Cola in all 3 stores, with positive significant estimates for 5 out of 8 new product dummies in the volatility equations. The results for the entire cola category in Table 2.8 show that all estimates related to the NPI variables in the sales volatility model were positive with significant results in 25 out of 49 estimates. The general rise in sales volatility following NPI is also confirmed by the combined, meta-analytic results using the method of adding Z's (Rosenthal 1991) with a significant positive impact across all brands (meta Z=10.435; $p < 0.01$). Interestingly, it seems that the effect of the new brand entry (i.e., Red Bull) at Kaufland ($\tau_{131} = 3.299$, $p < 0.01$) and Rewe ($\tau_{131} = 2.349$, $p < 0.01$) both generated an even higher increase in Coca Cola's sales volatility than its own brand innovations (i.e., τ_{121} for Coke Zero and τ_{122} for Coke Light Plus) at the respective stores. In Table 2.8, we observe the same positive impact of product entry on sales volatility of competing brands and the retailers' private label. Specifically, the meta-analyses confirm a positive and significant effect of NPIs on own brand sales volatility (Coca Cola meta Z=9.421; p <0.01) and competing brand volatility (meta Z=9.736, p <0.01) for all four national brands as well as the retailers' private label. The positive effect of the new brand Red Bull on brand sales volatility is also confirmed (meta Z=12.957, p <0.01).

The relation between volatility and sales levels. Table 2.7 further shows for Coca Cola sales that higher volatility in sales following NPI is responsible for higher (not lower) future sales levels. This conclusion is based on the estimates for ζ_{11} of the (lagged) volatility variable in the sales level model (salesvol(-1)), that is positive and significant, except for retailer Rewe. As can be seen in Table 7, this result is strikingly consistent across brands and retailers, with all positive estimates except one that are significant for 11 out of 25 estimates. Also the meta-analysis confirms this positive relationship (meta Z=12.23; $p < 0.01$).

2.7.3 Model findings all categories

The cola results are consistent with the results from the remaining eight product categories, providing us strong support that an NPI leads to an increase in sales volatility of own and competing brands and that such volatility is associated with an increase in future sales level for the brands. Table 2.9 summarizes the number of models with positive (significant) estimates for the impact of NPI on sales volatility (derived from the new product entry variables in the GARCH models) and for the impact of volatility on brand future sales levels (derived from the lagged sales volatility variable in the VAR models), respectively. All of the 821 model estimates on the impact of NPI on sales volatility are positive, with 427 (52%) of them statistically significant (significance tests always at $p < 0.10$, 1-sided). Model estimates for the impact of volatility on mean sales level are also consistent across categories, with 212 out of 214 estimates positive and 107 (50%) that are significant. The average effect size is the highest for yoghurt category (0.39) and the lowest for diapers (0.18). To make these estimates more comparable across product categories with different household spending levels, we standardized model estimates by multiplying the model estimates (i.e., ζ_{11} in Eq.5) with the ratio of standard deviation of sales volatility (i.e., $\hat{\mathrm{h}}_1$ in Eq.5) and sales level ($\zeta_{\mathrm{std}} = \zeta_{11} \times SD(\hat{\mathrm{h}}_1)/\mathrm{SD}(\mathrm{Sales})$). Figure 2.3 shows that the positive impact of sales volatility on the mean sales level of a brand is the strongest in the diapers category (0.551) and weakest in crisps (0.056). On average, a 1 standard deviation increase in sales volatility will, on average, lead to a 0.23 standard deviation rise in brand sales level.

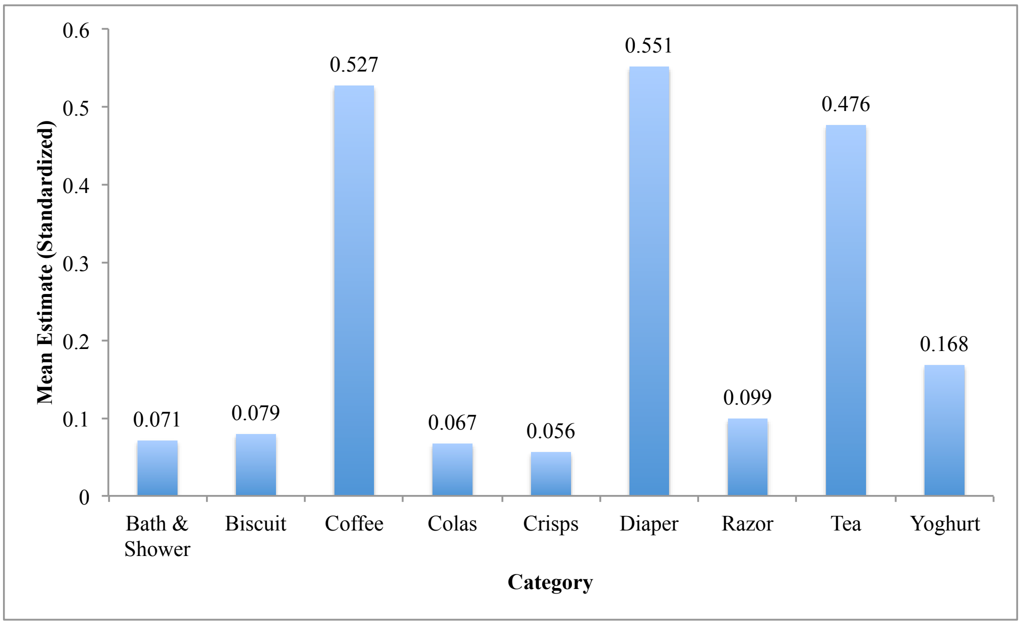
Overall, the consistent multi-innovation, multi-brand, multi-retailer model results indicate that our findings are robust across innovations, brands, and retailers, and they are not subject to unobserved time-invariant factors at any of those levels. Furthermore, since the same product is often adopted by retailers in different weeks, we can assure that our findings are not affected by unobserved time-specific factors either.

Table 2.9 Frequencies and Mean Estimates of Impact of NPI on Sales Volatility and Impact of Sales Volatility on Brand Mean Sales Level across Categories

Category	NPI → Sales volatility		Sales volatility → Mean Sales level		
	Positive effect	Significant positive	Positive effect	Significant positive[b]	Mean estimates
Bath & Shower	96/96	59/96	29/29	12/29	0.21
Biscuit	91/91	42/91	20/20	14/20	0.28
Coffee	143/143	68/143	29/29	16/29	0.27
Colas	49/49	25/49	24/25	11/25	0.29
Crisps	91/91	51/91	29/29	16/29	0.22
Diapers	72/72	42/72	14/14	7/14	0.18
Razor	47/47	24/47	17/17	9/17	0.39
Tea	133/133	57/133	25/26	10/26	0.32
Yoghurt	99/99	59/99	25/25	12/25	0.39
Total	821/821	427/821	212/214	107/214	

Notes: we report the No. of positive estimates /Total no. of estimates in each category as well as the No. of significant estimates (p-value < 0.10 1-sided) /Total no. of estimates in each category. The mean standardized estimates in each category are reported where each estimate is multiplied by the ratio of standard deviation of sales volatility and standard deviation of sales.

Figure 2.3 Standardized Model Estimates for the Impact of Sales Volatility on Sales Level by Category



Note: Standardized values are obtained by multiplying the model estimates (i.e., ζ_{11} in Eq. 5) with the ratio of standard deviation of sales volatility (i.e., $\hat{h}_1$ in Eq.5) and sales level (Sales). $\zeta_{std} = \zeta_{11} \times {}^{SD(\hat{h}_1)}\!/_{SD(Sales)}$.

2.7.4 Drivers of innovation-induced volatility

Of the 821 estimates that capture the change in brand sales volatility at the retailer after NPI, 141 estimates relate to the entry of a completely new brand (i.e., τ_{13m}), 472 related to own brand innovations (i.e., τ_{12n}), and the remaining 208 capture the impact of competing brand innovations (i.e., τ_{14}). These estimates are linked in a second stage analysis using Eq. 6 to the proposed drivers to explain when and for what brands volatility will increase most after entry. In our model estimation, we further account for three issues.

First, because the dependent variable contains estimated coefficients, we first check for heteroscedasticity of the Ordinary Least Square model standard errors (Nijs et al., 2001). The White test indicated that the hypothesis of no heteroscedasticity was rejected (p <0.01), so WLS regression is used to estimate Eq. 2.6. Second, multicollinearity is not a concern given the maximum VIF value of 2.38 (mean VIF being 1.67). Third, given that innovation success in case multiple competing brands enter the store combines the performance across competitor innovations (instead of the performance of a single new product as with own brand innovations and new brands), we allow in Eq. 2.6 for an interaction between the competing new product dummy (*dCOMNP*) and innovation success (*INVSUC*).

The WLS model results are summarized in Table 2.10, Model 1. In addition, next to our main model, we also report the results (see Model 2) for a sample with only volatility estimates for the own brand innovations and new brands launches based on NPI dummies while omitting the competing brand estimates (which were obtained from a count variable in case of multiple competing innovations). The results for both models are quite comparable, so we focus our discussion on Model 1.

The proposed drivers are well able to explain the extent to which innovations impact brand sales volatility. First, especially the type of innovation is important. The launch of a completely new brand in a category results in the biggest shifts in consumer preferences: it is responsible for a rise in volatility that exceeds the rise from own innovations by the focal brand (= baseline) (c1 = 0.680, p <0.01). New products launched by competitors, in contrast, are mostly less influential on sales volatility than own-brand innovations (c2 = -0.064, p <0.01). Interestingly, the absence of a main effect for the innovation success variable suggests that even less successful own innovation and new brands have the potential to boost sales volatility. For competing brand innovations, in contrast, the level of success is important, and it will strengthen the impact on sales volatility considerably, as we find a positive and large interaction between *dCOMBRD* and *INVSUC* ($c_{interaction}$ = 0.045, p < 0.01). This indicates that only successful innovations from a competitor can motivate consumers to try out other offerings and reconsider their habitual brand choice, triggering higher levels of turbulence.

At the brand level, a positive impact of the price premium variable (c4=0.015, p = 0.02) indicates that innovations from a high-equity brand receive more attention and result in more switching, perhaps because of larger marketing budgets and supports around product launch to break habits. Volatility is threatening small market players slightly more than leading brands since the *BRDRANK* variable is negative with weak significance (c5 = -0.007, p = 0.09). Brands with an innovative reputation tend to attract more consumer switching, as we find a positive effect of brand innovativeness on its sales volatility (c6 = 0.018, p < 0.01).

Finally, also the retail environment is driving consumer brand switching patterns after innovation launch. Consistent with our arguments on assortment composition and differentiation, an innovation by a national brand has a stronger impact on the brand's sales volatility at retailers with a larger assortment size (c9 = 0.286, $p < 0.01$). Finally, innovations lead to more volatile sales at retailers where private labels dominate (c10 = 0.127, $p < 0.01$).

Table 2.10 Weighted Least Square Regression Results

Variables	Model 1 All innovations	Model 2 Own brand innovations & new brands	Model 3 Validation
Innovation drivers			
dNEWBRD	**0.680*****	**0.686*****	**0.579*****
	(0.026)	**(0.027)**	**(0.037)**
dCOMNP	**-0.064*****		**-0.050****
	(0.017)		**(0.017)**
INVSUC	1.477	0.221	**3.775*****
	(1.475)	(2.901)	**(0.590)**
dCOMNP X INVSUC	**0.045*****		**0.039*****
	(0.006)		**(0.006)**
Brand drivers			
BRDPREM	**0.015***	0.010	**0.049*****
	(0.007)	(0.020)	**(0.010)**
BRDRANK	**-0.007***	0.006	**-0.008***
	(0.004)	(0.011)	**(0.005)**
BRDINV	**0.018*****	-0.001	**0.017*****
	(0.003)	(0.009)	**(0.003)**
Retailer drivers			
RETCONC	0.059	**0.709*****	0.066
	(0.059)	**(0.165)**	(0.065)
RETPROM	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
RETASSOR	**0.286*****	**0.253*****	**0.290*****
	(0.062)	**(0.070)**	**(0.062)**
RETPL	**0.127*****	**0.293*****	**0.168*****
	(0.031)	**(0.078)**	**(0.033)**
Controls			
dDISC	**0.070***	0.110	0.064
	(0.040)	(0.107)	(0.040)
dFOOD	-0.036	0.101	**-0.044****
	(0.015)	(0.070)	**(0.016)**
Constant	0.225	-0.319	0.265
	(0.264)	(0.278)	(0.266)
Observations	821	613	635
F statistics	$F(13,807)=201.09^{***}$	$F(11, 601)=161.89^{***}$	$F(13,621)=174.80^{***}$

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (p-values 1-sided)

Notes: Standard errors in parentheses. The dependent variable contains estimates obtained from the first stage analysis and reflects the change in brand sales volatility at a retailer after a new product launch. The model is estimated using WLS with all variables weighted by the inverse of the standard error of the dependent variables.

2.7.5 Model validations

Our results turn out robust to various alternative specifications of the models and variables, and they were not sensitive to the data period.

Alternative new product screening approach. We adjusted our screening approach and analyzed only the top three (instead of the top five) national brands in each category. This reduced the sample to 139 innovations (with 129 new sub-brands and 10 new brands). Having re-estimated our models for the top three national brands and the private label across nine product categories, we obtain consistent results supporting our formal propositions. Specifically, across the 159 models, we find 633 out of 635 positive estimates for the effect of NPI on sales volatility, with 322 (50.71%) statistically significant. Also, all 159 estimates for the effect of (lagged) sales volatility on sales level are positive, among which 108 (67.92%) are statistically significant. We then re-estimated the second stage WLS model using the 635 estimates. Results in Table 2.10 (Model 3) show that our model estimates are largely consistent in terms of sign and significance, validating our earlier findings.

Removing the most successful innovations. Our dataset shows that innovations differ greatly in terms of their market performance, with the best performing one achieving 9% market share during its first year of launch, while the average level is only 0.7% (see summary statistics in Table 2.3). To rule out that our results are driven by few exceptional innovations, we re-estimated all models after excluding the best-performing innovation with the largest market share in each product category. Again, results indicated that sales volatility induced by NPI has a positive impact on sales level (756 out of 758 estimates positive, with 402 significant) and that such new product induced volatility has a positive impact on future brand sales levels (211 out of 214 estimates positive, with 112 significant).

2.8 Discussion

Apart from its beneficial effects on brand sales performance, the introduction of a new product in the market can be an important source of concern to managers if it results in higher uncertainty and a significant rise in sales volatility over time. From an operational perspective, more volatile sales is undesirable for manufacturers who face difficulties in planning production, while also retailers will experience increasing inventory complexity and costly stock-outs with larger sales swings. However, from a demand perspective, we provide theoretical arguments that large sales peaks followed by steep drops in brand sales could have both positive and negative effects on subsequent sales levels and future demand.

This study confirms empirically based on a broad sample of 182 innovations from 9 different CPG categories that an NPI is indeed responsible for a rise in sales volatility for the innovating brand as well as its competing offerings within the same retailer. The increase was larger for own brand innovations compared to competing brand innovations, but the biggest rise in volatility was induced by the entry of an entirely new brand in the category. This rise was significantly positive for 73 (51.77%) of the estimates related to new brand entries, and for 232 (49.15%) own brand innovations estimates, and for 122 (58.65%) estimates related to competing brand innovations. Interestingly, the observed rise in volatility and uncertainty in brand sales at the retailer following the product launch did not inhibit brand sales performance in later periods. On the contrary, it was associated with faster adoption for the innovating brands and higher total sales levels over the subsequent period. Standardizing model estimates across nine product categories show that, on average, a 1 standard deviation increase in brand sales volatility leads to a 0.23 standard deviation increase in the series underlying sales level. This positive volatility-performance relationship was not only found for own brand innovations but also competing brands, and the retailers' private label benefited from new product entry and could grow their future sales levels, presumably through a rise in category attention through more marketing activity and beneficial price developments.

Finally, our drivers were able to explain a substantial part of the variation in these volatility changes. Combining all findings, we demonstrate that, in line with entrepreneurship studies by DiGregorio (2005) or Hmieleski and Baron (2008), brands whose sales are more vulnerable to NPIs are also the ones with the biggest potential to benefit from the sales volatility to enhance their long-run performance. Overall, findings from this paper challenge conventional marketing wisdom that competitor innovations are always bad for a brand and that sales volatility should be avoided after innovation launch.

2.8.1 Research Implications

Volatility has become a central concept in marketing lately, and several recent studies by Fischer, Shin, and Hanssens (2016) or Estaban-Bravo, Vidal-Sanz, and Yildirim (2017), for instance, have shown marketing's potential to influence volatility. These studies encourage managers to use marketing actions to smooth volatility in demand to diminish the excess operational costs and production inefficiencies associated with high(er) volatility. Our results, however, show that from a demand perspective, this advice may not always be justified. On the contrary, large sales swings following a new product launch can also be good news for brand managers (even from competing brands) and retailers because they can lift total or cumulative sales due to an expansion in category demand while it opens a window of opportunity to acquire customers that did not buy your brand before. These beneficial demand effects from increased sales volatility in the context of NPIs suggest that managers should not always intervene and certainly not smooth sales swings in all instances. Instead, managers could capitalize on the higher volatility to achieve larger sales levels over the same period by stimulating product trials and luring new customers to enter the market, some of which might stay. With these new findings, manufacturers and retailers should be in a better position to trade off the negative operational costs of more uncertainty in sales against the demand rewards from higher total sales levels after launch.

Secondly, our study focuses on not only on the innovating mother brand but also major competing national brands at the retailer that are faced with the NPI. Therefore, beyond what we discussed above, managers of competing brands should not feel too threatened by NPIs by other brands and react immediately with aggressive strategies to defend their customers from switching away. Instead, our findings indicate that brands may also benefit from a competitor's NPI due to a positive externality of the NPI and category expansion. Managers of competing brands should evaluate how to best make use of the NPI together with the volatility brought by it, so that the overall impact on their sales can be maximized.

Thirdly, our findings provide useful insights to managers, whether and when brand sales volatility will rise when new products enter. This is particularly useful in managing production (for manufacturers) or inventory levels (by retailers). The launch of a new brand in a CPG category triggers more intensive consumer switching, reflected in a higher rise in sales volatility than own-brand innovations. In contrast, brands are less vulnerable towards competitor NPIs, unless these entries are highly successful. But apart from innovation factors, also brand and retailer-context variables influence consumers switching and hence, induce higher volatility in brand sales. Innovations launched by brands that are priced at premium or more innovative brands tend to attract more consumer attention and switching through heavy marketing and a good track record. Also, innovations that enter retailers where private labels dominate induce higher volatility by catering to consumer tastes that are not matched by established private label offerings with limited differentiation. Finally, new products launched at retailers offering larger assortments tend to generate higher volatility since competition between national brands make consumers less loyal and more variety-seeking.

2.8.2 Limitations and Future Research

Our study has several limitations. First, our focus was on the volatility in volume sales (or quantity), as this is the basis for planning manufacturer operations and setting retailer inventory levels. But larger sales volume could be offset by lower prices at which the offerings are sold, especially when price patterns change too. In this context, volatility in sales revenues or the impact of sales volatility on profits deserves more research attention.

Second, while we established empirically that innovation launch could directly influence volatility and subsequent mean sales, establishing causality in a non-experimental setting remains challenging and requires further analysis to dig deeper into the drivers of the directional effect. Part of this effect was argued to take place due to adjustments in marketing activity around launch time by the innovating brands and/or their competitors. Although we formally accounted for prices and promotions in our analysis, we do not trace back what part of the volatility changes can be attributed to each of these different marketing (price) adjustments and whether this leads to more impactful marketing actions around product launch.

Third, we studied NPI and the subsequent volatility implications in the CPG industry where large sales peaks around launch will foster more trial purchases that could convert into repeat purchases and speed up sales takeoff. Future research is called for to assess these relations in other industries like consumer durables that are less dependent on repeat purchases.

Fourth, we assessed the impact of a new product once it becomes available at the retailer. But new products may influence sales volatility of incumbent brands at a store, even if it is not listed there. We leave these cross-store store volatility effects as an area for future research.

Finally, more research should evaluate if the incremental operational costs from a rise in sales volatility are indeed (more than) offset by the gains from higher demand induced by more volatile brand and category sales. This requires a careful profit analysis based on sales and margin data for individual brands in combination with details on the operational costs from production inefficiencies and inventory management. Such detailed data are hard to acquire at the brand level and even harder for the entire category at individual retailers. Similarly, competitive brands that typically suffer from negative performance effects when new products enter could still benefit from a rise in sales volatility when total category demand expands and new buyers try their offering. Again, to what extent these effects net out is subject to future study. Nonetheless, the consequences of sales volatility need to be considered both in the operational (supply) and demand domain. We hope our research will stimulate a more balanced debate on the impact of sales volatility and its consequences on brand and firm performance for various industry participants in different positions in the supply chain.

CHAPTER 3

Essay 2: Be A Spark Not A Backfire: Negative Emotional Appeal, Consumer Processing Disfluency and Click-Through of Digital Display Ads

Abstract

Digital advertising has become the biggest advertising sector, yet what drives consumer attention and motivates them to click remains an open question. Flooded by display ads while browsing online, consumers nowadays are getting frustrated and actively blocking ads to reduce their exposures. It is imperative for digital marketers to strike a healthy balance between capturing consumers' attention and keeping them unannoyed. Building on affect-cognition and fluency theories, we contend that negative ad appeals cost more cognitive efforts to process and induce consumer processing disfluency. Surprisingly, such disfluency does not backfire and trigger annoyance but instead ignite consumer interests and lead to a higher level of click and purchase intention and ad liking. The effect of negative appeals on disfluency seems more salient with utilitarian than hedonic goods. Further, our results highlight that ad effectiveness owing to disfluency may be at the expense of long-term brand image, posing a certain trade-off for marketers between short-term ad effectiveness and long-term brand performance.

3.1 Introduction

Digital advertising is a major marketing tool for brands to engage with consumers and motivate their adoptions. In 2019, total digital ad spending in the US reached $129.3 billion, surpassing traditional media spending for the first time[13]. The global total digital advertising spending is projected to reach $389 billion in 2021[14]. However, having become a business with an enormous size, how to make digital advertising effective is still under-exploited. Specifically, many digital ads have been massively evading consumers' online browsing

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13 https://pubmatic.com/wp-content/uploads/2019/12/2020-Global-Digital-Ad-Trends.pdf
14 https://www.statista.com/statistics/237974/online-advertising-spending-worldwide/

experience and competing for consumers' attention and engagement through a variety of tactics (Liu-Thompkins, 2019). Indeed, visual attention is always cited as the most critical reason for online ad clicking and conversions (e.g., Steele et al., 2013). Capturing attention is particularly a challenge for display ads since consumers' main task is not to browse the ads but the contents on the webpage. Consumer attention needs to be captured and shifted away from the contents to the display ads before click-through can happen ("immediate traffic", see Liu-Thompkins, 2019). Visual creative elements of ads that successfully draw consumer attention (e.g., ad size, color, and motion) can enhance positive brand perceptions (e.g., novelty, see Kim and Lakshmanan, 2015), brand recall and recognition (Baron, Brouwer, and Garbayo, 2014), and click-through intentions (Yaveroglu and Donthu, 2008).

However, attention-attracting tactics are double-sided swords for digital marketers. First of all, consumers are found less tolerant and understanding of attention-getting and engagement devices (e.g., intrusion) for online ads than for offline ads (Logan, 2013). They are also more likely to develop mental and physical avoidance of online ads (Baek and Morimoto, 2012). High volumes of ad exposures, especially repeated exposures, have caused consumer fatigue, irritation, and annoyance (Goldstein et al., 2014). Consumers tend to consider digital ads' attention-getting devices as intrusive or annoying, and even threatening their digital privacy (Goldfarb and Tucker, 2011). Further, consumers are said to have developed "ad blindness" and installed various ad-blocking software (Edwards et al., 2002; Baek and Morimoto, 2012).

Therefore, how to strategically design the creative elements of digital display ads to capture consumers' attention (i.e., to shift their attention from the primary task) to an appropriate extent so that the tactics do not backfire is the key tackling the challenge. While research on visual creative elements such as size, shape, color, and animation of digital ads has been vast (Pieters et al., 2010; Simola et al., 2013), there is a limited understanding of what and how emotional appeals may be most relevant to stimulate consumer engagement and ad clicking. Classic advertising literature argues that an ad engages with consumers via affect transfer, which refers to a carryover process that evokes consumers' similar feelings (MacKenzie et al., 1986). Hence, the emotional appeal of an ad is quite critical in that it may change consumer's emotions and, consequently, attitude towards the ad. Accordingly, previous studies have mostly found that advertisements with positive appeals elicit consumers' pleasant feelings, which then turn into a positive attitude towards the ad and even the brand (e.g., Eckler and Bolls, 2011; Pham et al., 2013).

However, the context of digital display ads has its uniqueness. While browsing online, consumers' primary task is not processing display ads but rather consuming the contents. An effective display ad needs first to capture consumers' attention and then engage with consumers to motivate their click-throughs.

We are hence interested in exploring ad creative design that can create a certain level of disruptions or "bumpiness" along consumers' browsing journey by shifting their attention from the very contents towards the ad (Yoo et al., 2004). Meanwhile, marketers need to make sure that consumers are not annoyed by such disruption (e.g., obtrusive ads). To this end, we bring in the notion of processing fluency. Processing fluency is defined as the subjective experience of the ease with which an incoming stimulus is processed (Graf et al., 2017). It is a perception that can be easily experienced when a person is exposed to a display ad. Accordingly, we contend that ad emotional appeals that elicit processing *disfluency* should accomplish the attention-capturing and engagement task.

The vast literature in marketing has provided evidence on the antecedents and consequences of processing disfluency. For example, a logo's visual complexity requires more cognitive effort for consumers to understand the business's nature, leading to higher processing disfluency (Miceli et al., 2014; Mahmood et al., 2019). When introducing and describing a new brand, complex linguistics cues are less often encountered in audiences' reading experience and are hence more priming (Oppenheimer, 2006). Consequently, linguistics as such is more disfluent to process. Further, stimuli that are considered less typical or prototypical are subject to higher processing disfluency (Graf et al., 2018; Winkielman et al., 2006).

In terms of consequences of disfluency, previous studies have mostly focused on the negative (positive) effect of disfluency (fluency) on attitudes and judgments since people appreciate the ease and convenience (Reber and Unkelbach, 2010; Song and Schwarz, 2009). On the other hand, more recent research has shed some light on how disfluency can generate positive effects. When designing a logo, visual asymmetry (versus symmetry) and complexity (versus simplicity) generate more processing disfluency, which surprisingly leads to a higher level of excitement, favor, and favorable judgments (Luffarelli et al., 2019a; Mahmood et al., 2019). Visual search literature contends that a non-focal object that exhibits more contrast with its surroundings is more visually salient and can capture more attention (Aribarg and Schwartz, 2020; Pieters and Wedel, 2004; Van der Lans et al., 2008). In the field of video ads, instead of offering a smooth affective experience, advertisers should "give people an emotional roller coaster" by alternating emotionally heavy and light points with breaks and gaps (Libert and Tynski, 2013). Recent industry research shows that compared with positive emotions, less commonly observed negative emotions such as sadness, sorrow, and anger can lead to the viral success of display ads (Forbes, 2017).

Therefore, we contend that ads with a negative emotional appeal are subject to a higher level of click-throughs because disfluency induced by the negative appeal is more effective in attention attraction and interest stimulation than a fluent processing experience. Nevertheless, there have been no empirical studies that formally examine the impact of ad emotional appeal on processing disfluency and the impact of disfluency on consumer ad clicking decisions.

This study focuses on (1) examine negative ad emotional appeal as an antecedent of disfluency, and (2) study the impact of processing disfluency induced by negative ad appeal on consumer ad click-through decisions, and finally (3) explore some boundary conditions, including product and service category (i.e., utilitarian vs. hedonic).

3.2 Literature and Hypothesis

3.2.1 Processing disfluency in digital advertising: Antecedents

Consumer's willingness to click on an online display ad is subject to a variety of reasons. Extant literature has been vast, investigating the effect of ad creative elements that induce consumer click-through behaviours. Visual cues such as ad color, hue, saturation, and brightness (Greenberg, 2012; Lee and Ahn, 2012), size (Pieters and Wedel, 2004), display orientation (Simola et al., 2013), and background complexity (Pieter et al., 2010) can all capture consumer attention and induce ad clicking.

More recently, an emerging stream of research has started to recognize the perception of processing fluency as driving consumer's attitudes and reactions towards marketing communications initiated by brands. Processing fluency is defined as the subjective experience of the ease with which an incoming stimulus is processed (Graf et al., 2017). While exposed to advertisements, consumers' processing fluency can be induced by a variety of creative elements. For example, previous studies have found that visual clarity, illuminance, shape, color, font size, facing directions, and materiality can all capture consumers' attention and influence their perception of fluency (Forster et al., 2016; Landwehr et al., 2011; Leonhardt et al., 2015). These antecedents of fluency Besides visual stimuli described above, emotional appeals of ads can also attract attention and engage with consumers (Liu-Thompkins, 2019). However, there seems a lack of research that studies the impact of ad emotions on consumer processing fluency.

3.2.2 Ad emotional appeal and processing fluency

Emotional appeals can influence consumers' cognition and, ultimately, behaviour by influencing how information is processed (Forgas, 2008). Emotional appeals of advertisements influence people mainly through affect transfer, which is a carryover process that evokes consumers' similar feelings (MacKenzie et al., 1986). Further, research shows that positive moods lead to less effortful processing because people in a good mood tend to avoid cognitive effort (Schwarz and Bless, 1991). As a result, extant literature has studied various positive emotional appeals (e.g., warmth, passion, joy, humor, and excitement) together with their positive impacts on consumer ad attitudes and behaviours (Borah et al., 2020; Li et al., 2017; Luffarelli et al., 2019b). In contrast, theories suggest that negative emotions promote more effortful and vigilant processing (Schwarz, 1990; Forgas, 2017).

Looking at the literature, several theories support the notion that negative emotion can lead to a lower (higher) level of ad processing fluency (disfluency). Firstly, negative appeals increase processing latencies and result in higher memory accuracy and greater attention to concrete details of people (Forgas and East, 2008; Forgas et al., 2009). Affect-cognition theories also suggest that negative affect can promote a more concrete and vigilant information processing style, which involves more detailed attention to the content of a communicative message (Matovic et al., 2014). Secondly, the broaden-and-build theory indicates that in contrast to positive emotions that "broaden" people's though-action repertoires, negative emotions do the opposite; however, negative emotions can induce more specific action tendencies hence closer attention and focus (Fredrickson, 2001). Furthermore, linguistic processing research indicates that negative mood produced longer and more attentive processing (Matovic et al., 2014). This is because a negative mood can improve people's understanding of information by detecting information ambiguity more effectively.

Given that processing disfluency is induced by higher level of cognitive efforts and attention spent in information processing, our first hypothesis is about how negative emotional appeals of display ads can lead to higher level of processing disfluency:

***H1**. Compared with positive emotional appeals, a negative emotional appeal of digital display ads leads to a higher level of processing disfluency.*

3.2.3 Disfluency and consumer click-through

The impact of processing disfluency on consumer ad clicking is not clear since theories on both a positive and a negative impact can be forwarded—an ample amount of research on processing fluency arguing that people appreciate the fluent experience. People rate fluent stimuli more positively in terms of trust, truthfulness, liking, to name a few (see a summary in Alter and Oppenheimer, 2009). Besides, fluent stimuli tend to positively influence people's perceptions since they typically more frequently encountered in people's experiences hence more conceptually priming and familiar (e.g., Chae and Hoegg, 2013; Landwehr et al., 2013). Such phenomenon is also described as the "beauty-in-averageness" effect, where people prefer highly prototypical stimuli when judging an unfamiliar product, brand, or person (Landwehr et al., 2011; Winkielman et al., 2006).

However, on the other hand, an emerging stream of research has started to address the positive impact of disfluency, which is supposed to be more stimulating and arousing. For example, product arrangements that are unsystematic hence contradict one's expectation, trigger a more extensive exploratory product search and result in a higher likelihood of purchasing an unfamiliar product (Walter et al., 2020). Similarly, disfluent cues disrupt people's habitual processing and lead to inferences of specialness, task importance, and interest (Graf and Landwehr 2015; Labroo and Pocheptsova 2016; Pocheptsova et al., 2010).

Given arguments on both a positive and negative impact of disfluency on consumer's willingness to click on digital ads, our second hypothesis is written as:

H2a. *Consumers are less likely to click on a digital display ad with negative emotional appeal. This effect is mediated by processing disfluency.*

H2b. *Consumers are more likely to click on a digital display ad with negative emotional appeal. This effect is mediated by processing disfluency.*

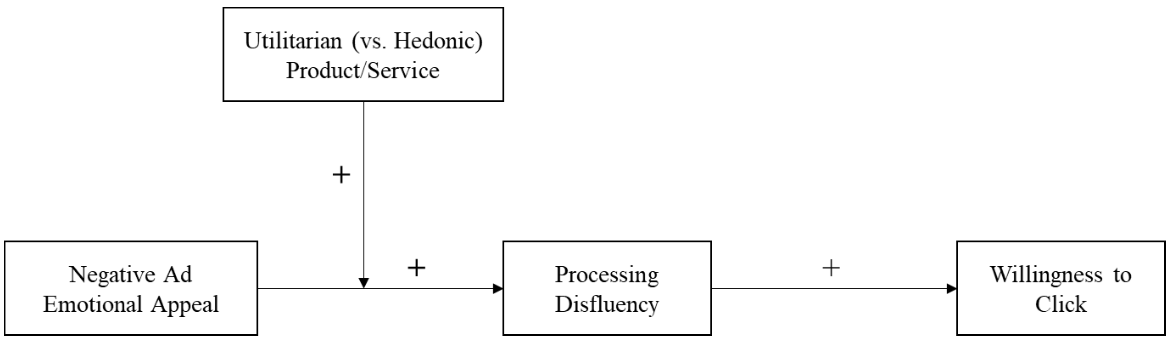
3.2.4 The moderating role of produce/service category: hedonic vs. utilitarian

Hedonic goods are defined as those "whose consumption is primarily characterized by an affective and sensory experience of aesthetic or sensual pleasure, fantasy, and fun" (Hirschman and Holbrook, 1982). In contrast, utilitarian goods consumption is more "cognitively driven, instrumental, and goal-oriented and accomplishes a functional or practical task" (Strahilevitz and Myers 1998). Prior research has generally reached the consensus that hedonic consumption is more emotionally driven while utilitarian consumption is more cognitively driven (Kronrod and Danziger, 2013). Given that processing disfluency is induced by more cognitive effort, utilitarian goods, compared with hedonic goods, are more cognitively driven and intrinsically require more cognitive efforts. Therefore, we expect that the impact of negative emotional appeal on processing disfluency should be stronger for utilitarian products or services.

H3. *The ad category moderates the impact of negative ad appeal on processing disfluency so that a utilitarian ad's negative emotional appeal has a stronger impact on processing disfluency than a hedonic ad.*

The theoretical framework of this paper is summarized in Figure 3.1. To examine our hypotheses, we combine a series of lab experiments in conjunction with a field study enabled by the availability of a rich dataset on consumer ad impression and clicking (Liu-Thompkins and Malthouse 2017; Malthouse and Li 2017). We present four studies. The first is a preparatory study that asks people to rate and comment on a representative sample of ads. The goals of this study are to generate stimuli for the two subsequent experiments. In Study 1, we formally examine the mediation role of processing disfluency in bridging negative ad appeal and consumer willingness to click on an ad. Study 2 replicates Study 1 using an advertisement from another product/service category and examines the moderating role of the service category (i.e., hedonic vs. utilitarian). Finally, in Study 3, we replicate our main findings from experimental studies by estimating a dynamic factor model (DFM) on field data.

Figure 3.1 Theoretical Framework



3.3 Preparatory Study: Assessment of Ad Emotional Appeal

This preparatory study aims to generate stimuli of display ads with positive and negative emotional appeal for use in the next two formal studies. We picked warmth and fear as the positive and negative emotional appeal to study. Both appeals are well-established in the literature and have been found effective persuasion mechanisms in the advertising context.

Warmth is a “positive, mild, volatile emotion involving physiological arousal and precipitated by experiencing directly or vicariously a love, family, or friendship relationship” (Aaker et al., 1986). Fear appeals refer to messages containing “some sort of threat” (Brooke, 1981). Following previous studies that examined warmth and fear as emotional appeal in experimental studies (Aaker and Bruzzone, 1981; Wells et al., 1971), we manipulated emotional appeal through the texts in the ads.

To make sure that we identify the design of stimuli with the strongest contrast in perceived warmth and fear of participants, we manipulated the length of texts. As a result, we have a 2 (emotional appeal: warmth vs. fear) x 2 (text length: long vs. short) design for the test. We created four versions of display ads of a fictitious brand (PrimeHoliday.com, which is a travel service website) corresponding to the four conditions. For example, in the “warmth x long text” condition, the ad says, “*Get your perfect holiday feeling! Book your hotel via our website and enjoy your stay at one of the world’s best hotels.*”, while in the “fear x long text” condition it says “*Protect yourself against being hijacked of your holiday! Book your hotel via our website now and secure your room in one of the world’s best rated hotels before it’s too late!*” (see Figure 3.2).

Figure 3.2 Example Stimuli for Positive (Warmth) and Negative (Fear) Appeal

(a) warmth x long (b) fear x long

This study was conducted on Amazon.com’s Mechanical Turk (MTurk) online labor market. Experiment participants were paid $1 each. Since our manipulation lies in language, this task was restricted to participants located in the U.S., U.K., Canada, and Australia, where English is the native and official language.

We recruited a hundred and twenty participants and randomly assigned them to one of the four conditions. After viewing the ad, participants are asked to rate the ad on the perceived level of warmth, fear, and four other emotional appeals frequently studied in the literature (joy, humour, offensiveness, anger). Table 3.1 summarizes the average rating of each appeal by the length of texts. We compare the contrast between positive (warmth) and negative (fear) appeal within long and short texts conditions and summarize the p-values of two-sample t-tests. Table x shows that the contrast between warmth and fear in the long-texts versions of stimuli is statistically significant ($p_{warmth} = 0.037$, $p_{fear} = 0.032$). There is no significant difference in participants' ratings on other appeals (p-values greater than 0.05). Therefore, we are confident that our manipulation of warmth and fear appeals work and that we use the stimuli with long texts (i.e., "warmth x long" and "fear x long") in our formal study.

Table 3.1 Preparatory Test—Summary of Results

	Long texts			Short texts		
Stimuli	Fear	Warmth	p-value	Fear	Warmth	p-value
(Mean)						
Joy	4.333	4.875	0.210	4.481	5.294	0.128
Humour	4.133	3.750	0.980	3.778	4.441	0.233
Warmth	**4.050**	**4.938**	**0.037**	4.296	4.956	0.112
Fear	**4.250**	**3.109**	**0.032**	3.463	3.426	0.948
Offensiveness	4.100	2.938	0.056	3.000	4.059	0.070
Anger	3.867	3.000	0.133	3.148	3.441	0.621

3.4 Study One

The purpose of this experimental study is to examine the impact of positive and negative emotional appeals in ad creative on consumer processing fluency and then on their willingness to click. In other words, we are examining the mediation model of *negative (vs. positive) ad appeal→ processing disfluency →willingness to click on the ad*.

One hundred and six respondents (Mage 36-50 years; 35% female) were recruited on the online participant pool Amazon Mechanical Turk (MTurk). We used the display ads identified from the preparatory study in Figure 2.1 as the stimuli of this study.

3.4.1 Stimuli and Measurement

We randomly assigned participants to one of the two versions of ads (warmth vs. fear). Participants were informed that they would be shown a display ad and then invited to rate the measures based on their perceptions about the ad.

We asked participants to rate their perception of *processing fluency* of the ad on five nine-point scales presented in a random order (fluent, effortful, difficult, easy, comprehensible; 1=very low and 9=very high; adapted from Labroo et al., 2008; Graf, Mayer, and Landwehr, 2017). We averaged these scales into a single measure (α= 0.83). Next, we asked participants to rate their willingness to click on the ad and willingness to purchase the service on a nine-point scale, respectively (1=very low and 9=very high). We also asked participants to rate their attitudes towards the ad (good/bad, pleasant/unpleasant, favorable/unfavorable; 1=very low and 9=very high) and towards the brand (good/bad pleasant/unpleasant, like/dislike; 1=very low and 9=very high) on three nine-point scales presented in random order adapted from Bergkvist and Rossiter (2007), respectively.

We have also asked our participants to rate the information content (Meire et al., 2019), perceived service quality (Kirmani and Wright, 1989), and product involvement (Demirci et al., 2014). We find no statistically significant difference in results between the two groups of participants for familiarity, attachment, innovativeness, or uniqueness.

3.4.2 Manipulation check

We asked the participants to rate perceived warmth and fear on two nine-point scales (the ad is cozy/fearful, the ad sends out warmth/fear; 1=very low and 9=very high, adapted from Geuens et al., 2011; Olney et al., 1991; α_{warmth}=0.87; α_{fear}=0.92) As expected, participants assigned to the condition of warmth rated perceived warmth significantly higher (M_Warmth_{warmth}=5.29) than participants assigned to the fear condition (M_Warmth_{fear} = 4.72; t(106) =2.22, p = 0.03). Similarly, participants assigned to the fear condition rated perceived fear significantly higher (M_Fear_{fear}=4.64) than those assigned to the warmth condition (M_Fear_{warmth} = 4.09; t(106) =2.62, p = 0.01).

3.4.3 Results

We first present evidence for the direct effects of negative ad appeal on processing disfluency. We then report evidence for the serial mediation of *negative ad appeal → disfluency → willingness to click/purchase*.

In line with H1, participants rated the ad with fear appeal as more disfluent ($Disfluency_{warmth}$= 3.24, $Disfluency_{fear}$= 3.93; t=3.66, p<0.01). (see Figure 3.3 and 3.4). We then used the PROCESS method (Model 4, Hayes, 2017) to analyze the indirect effect of negative ad appeal on willingness to click and purchase through disfluency. We estimated the indirect effect of negative ad appeal using a bias-corrected confidence interval based on 5,000 bootstrap samples. Supporting H2b, our analysis showed that display ads with negative appeal were associated with a higher level of disfluency (β=.69***, t=3.61, p<0.01), which in turn was associated with higher willingness to click (β= .28*, t=1.75, p=0.08). The confidence interval of the indirect effect of negative appeal on willingness to click through disfluency excluded zero (95% CI: .05, .51), indicating a significant serial mediation. We did not find statistically significant support for the positive effect of disfluency on willingness to purchase (β=.09, t=.53, p=.60). Further, unrelated to the mediation model but quite crucial for our arguments, we compared the rated level of ad annoyance in the two groups and found no significant difference (M_{Fear}=4.685, M_{Warmth}=4.731, t=0.11, p=0.91). Such a result helps us address that processing disfluency induced by negative ad appeals will not cause consumer annoyance but rather create an "unharmful" break of consumers' flow of content browsing and shift their attention towards the ad.

Further, we also tested the impact of negative ad appeal on participants' attitudes towards the ad and the brand through disfluency. Using the same method, we find the support that the processing disfluency induced by negative ad appeal was associated with higher (more positive) attitudes towards the ad (β=.38, t=3.98, p<0.01) but lower attitudes towards the brand (β=-.81, t=6.12, p<0.01). Figure 3.5 provides a summary of the results we obtained in this section.

Figure 3.3 The Effect of Ad Appeal on Disfluency, Willingness to Click and Purchase

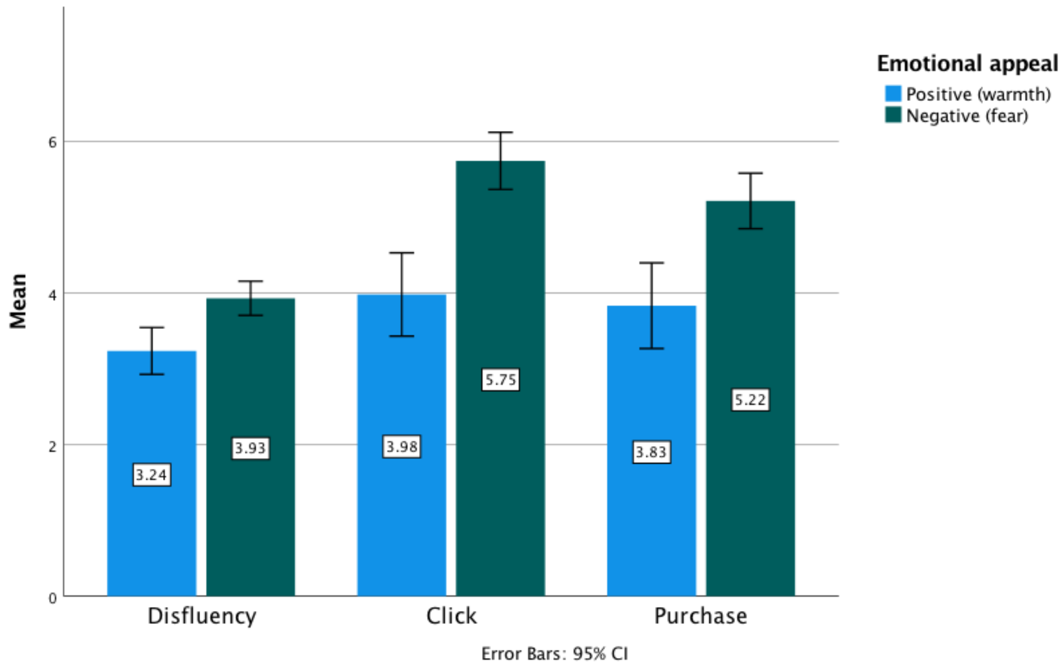


Figure 3.4 The Effect of Ad Appeal on Disfluency, Ad and Brand attitude

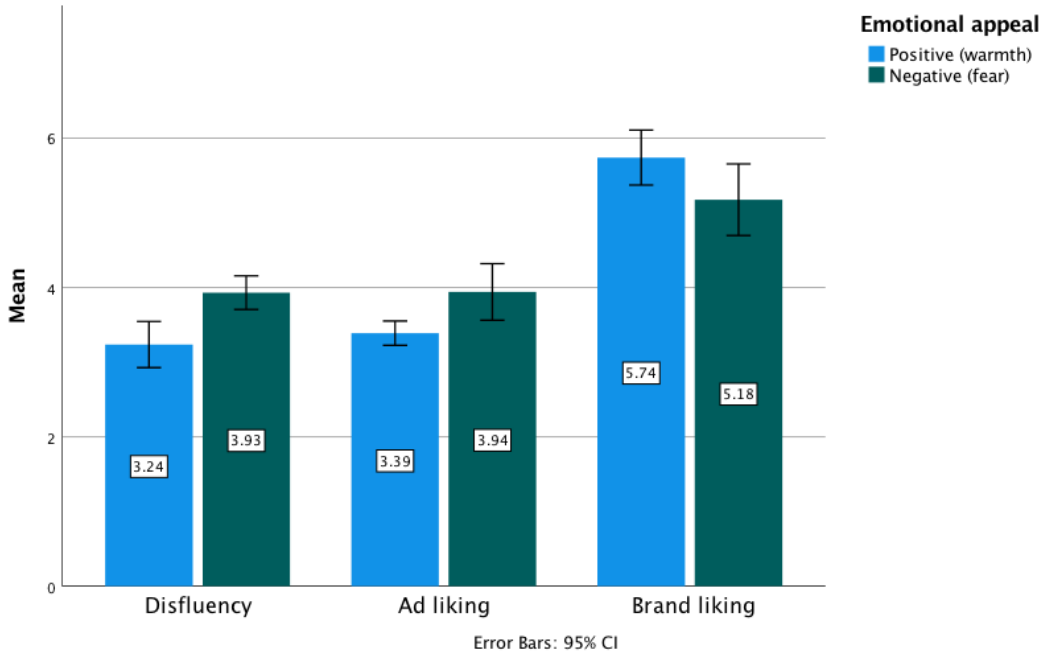
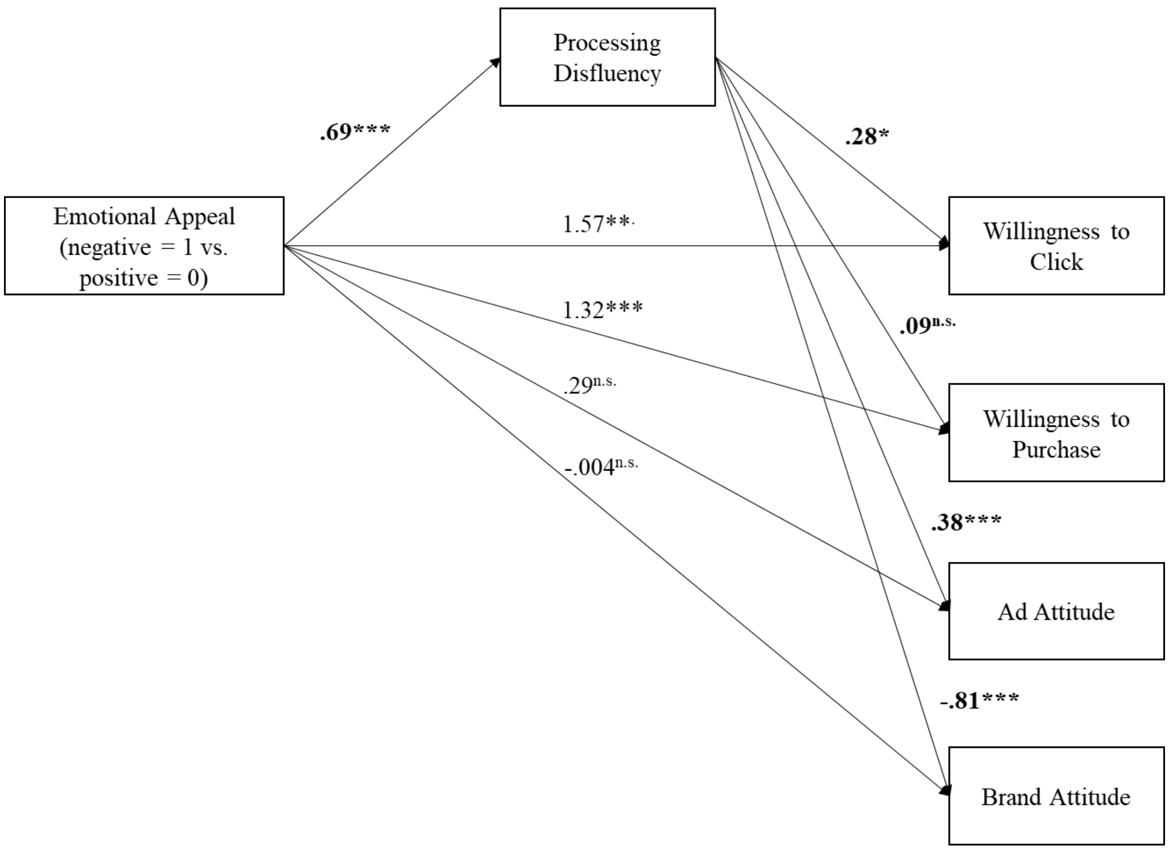


Figure 3.5 Study 1—Mediation model results summary



3.5 Study Two

The purpose of this study is twofold. Firstly, we replicate Study 1 using another category of service, which is an insurance service provider. Secondly, we examine H3, namely the moderating effect of product/service category (hedonic = travel vs. utilitarian = insurance).

One hundred and six respondents (Mage 36-50 years; 46% female) were recruited on the online participant pool Amazon Mechanical Turk (MTurk). We created warmth and fear conditions for display ads of a fictitious insurance company (Insurance24.com) specializing in fire insurance. In the positive (warmth) appeal condition, it says, "*Enjoy your life without any worries about house fires. We at Insurance24.com help you protect your house and family by finding the right fire insurance for your personal needs*". In the negative (fear) appeal condition, it says, "*House fires ruin the existence of more than 300,000 US citizens per year. Don't leave your house and family at life danger. Insurance24.com*".

Consistent with H1, we found that participants rated the ad with fear appeal as more disfluent ($Disfluency_{warm}$= 3.34, $Disfluency_{fear}$= 4.49; t=3.66, p<0.01). (see Figure 3.6 and 3.7). We again used the PROCESS method (Model 4, Hayes, 2017) to analyze the indirect effect of negative ad appeal on willingness to click and purchase through disfluency. Supporting H2b, display ads with negative appeal were associated with a higher level of disfluency (β=1.15***, t=5.33, p<0.01), which in turn was associated with a higher willingness to click (β=.37***, t=2.68, p<0.01). Although there is statistically significant support for the positive effect of disfluency on willingness to purchase (β= .26*, t=1.74, p=0.08), the confidence interval of the indirect effect includes zero (95% CI: -.82, .57).

Further, results indicated that the processing disfluency induced by negative ad appeal was associated with lower attitudes towards the brand (β=-.39, t=-2.78, p<0.01). However, there is no significant effect on ad attitude (β=.19, t=1.45, p<0.01). Figure 3.8 provides a summary of the results we obtained in this section.

Finally, combining data from Study 1 and 2, we can examine H3 using PROCESS method (Model 8, Hayes, 2017) to examine the moderating role of product/service category (hedonic vs. utilitarian). In line with H3, we found a significant moderating effect of utilitarian (vs. hedonic) product/service on the positive relationship between negative emotional appeal on processing disfluency (β=1.15, t=2.79, p<0.01). As expected, negative ad appeal creates a stronger impact on consumers' disfluency for utilitarian than hedonic goods since consumers exert more cognitive effort when processing utilitarian goods. We did not find a significant moderating effect of product/service category on the effect of disfluency on outcome variables (i.e., willingness to click, purchase, and attitudes towards the ad and the brand). Results of moderation models are presented in Appendix A (Figure A1-A4). Yet it is worth noticing that the negative impact of product/service category on outcome variables may weaken or even cancel out the positive moderation impact.

Figure 3.6 The effect of emotional appeal on disfluency, willingness to click and purchase

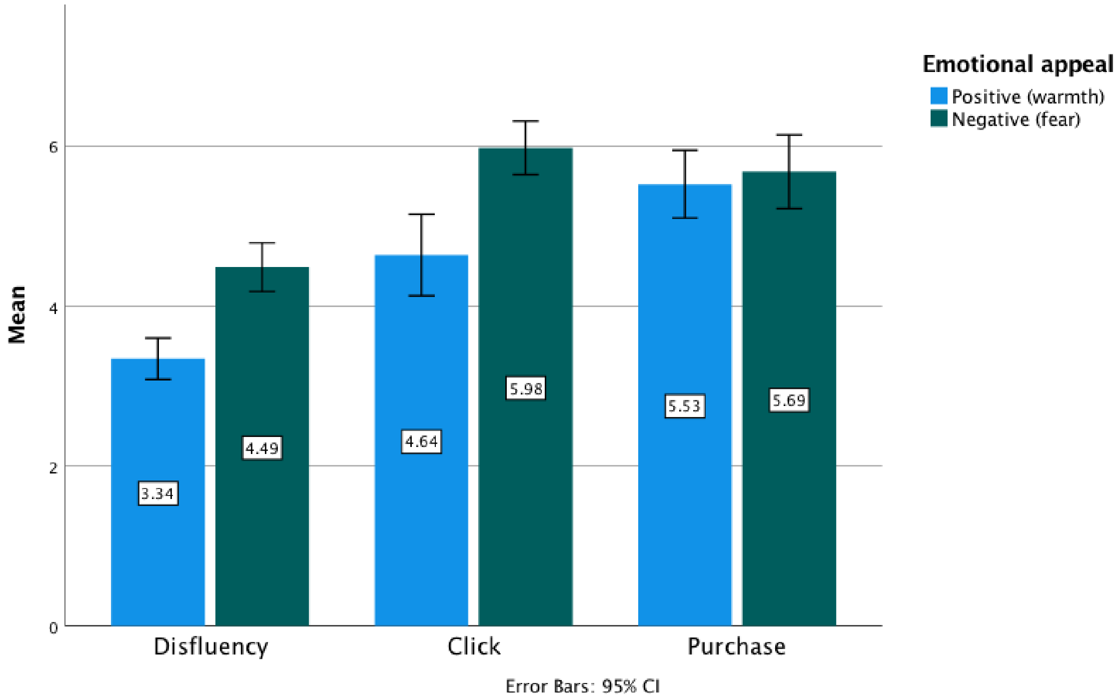


Figure 3.7 The effect of emotional appeal on disfluency, ad and brand attitude

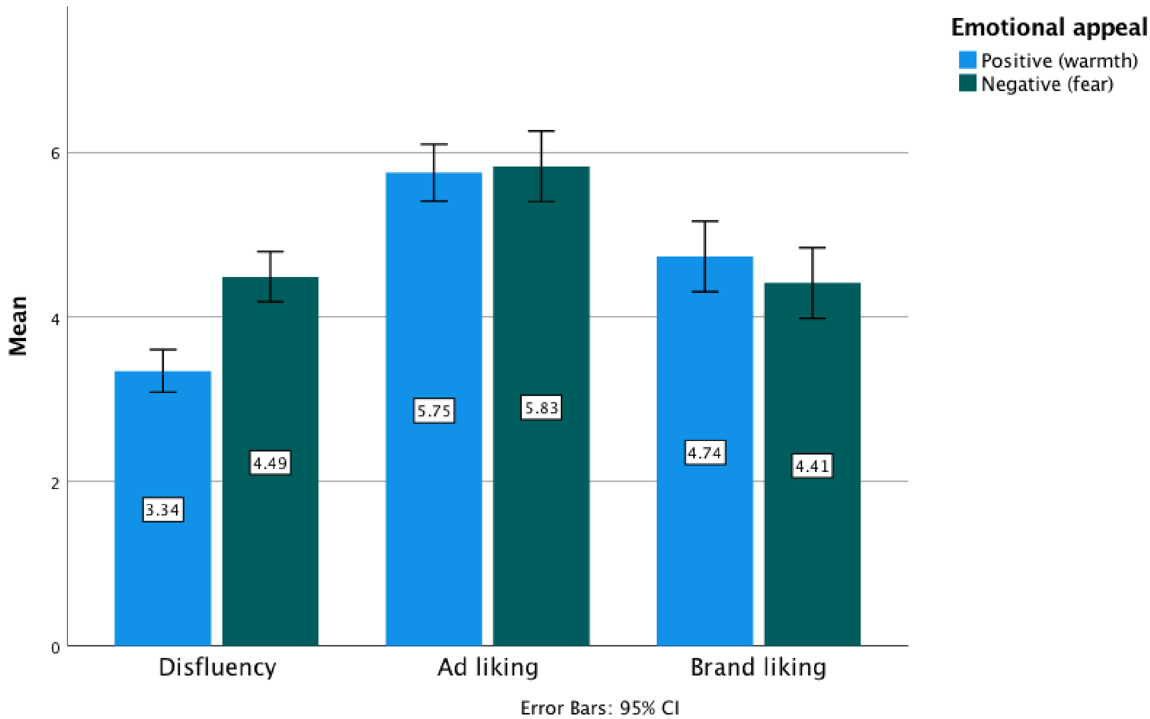
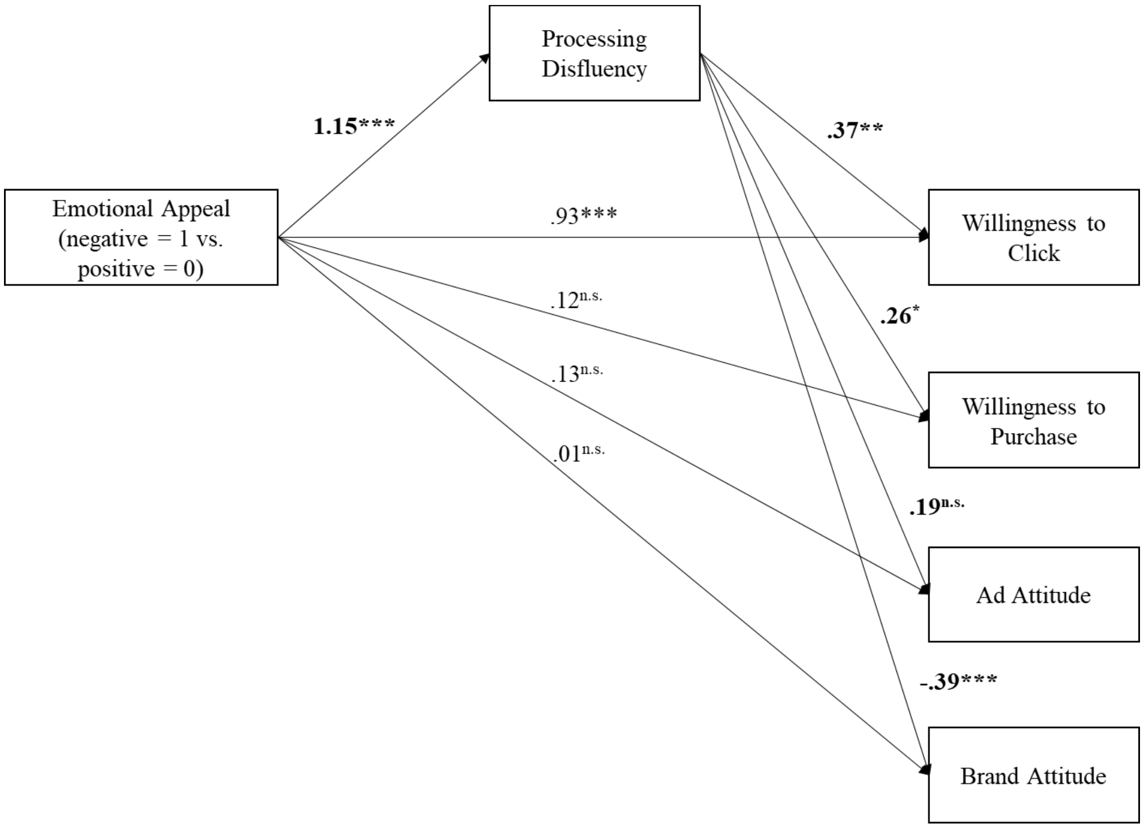


Figure 3.8 Study 2—Mediation Model Results



3.6 Study Three

Using data on actual consumer ad impressions and clicking, the purpose of this study is to replicate the results of our experimental studies in a field setting by showing that negative ad appeal is associated with processing disfluency, which then leads to higher willingness to click.

3.6.1 Model Requirements

Our research objectives impose several modelling requirements. First, we require a model that incorporates the intermediate factor, namely processing disfluency, as an unobservable factor and links the unobservable construct to observed consumer ad impressions and clicking. Second, the model needs to filter out the noise in measuring the unobserved factor to avoid inconsistent estimates and wrong inferences. Third, we need to model consumer disfluency as a dynamic construct that gets updated over time. Finally, consumers' processing disfluency is likely endogenous to ad impressions and clicking behaviours. Thus, we model the unobserved latent variable and consumer ad impressions and click-throughs as having a vector autoregressive process. Following Bruce et al. (2012), we are led to specify a Dynamic Factor Model (DFM).

3.6.2 Dynamic Factor Models

Dynamic Factor Models (DFMs) were developed and applied in economics (Sargent and Sims 1977; Watson and Engle 1983) but are still rather new to the marketing literature. DFMs have the following general form:

$$y_t = Qf_t + u_t \tag{3.1}$$

$$f_t = \sum_{p=1}^{P} A_p f_{t-p} + Bx_t + v_t \tag{3.2}$$

Equation 3.1 and 3.2 are called observation and transition equations, respectively. The observation equation captures the composition of the unobservable factor (here, in our case, disfluency). The transition equation models the dynamic evolution of unobservable factors. y_t is a $k \times 1$ vector of endogenous variables (e.g., consumer ad impressions and clicking behaviours), f_t is a $n_f \times 1$ vector of unobservable factors, Q is a $k \times n_f$ matrix of factor loadings, A_p is a $n_f \times n_f$ matrix of parameters for the autoregressive factors, B is a $n_f \times\ n_x$ matrix of parameters, x_t is a $n_x \times 1$ vector of exogenous variables (e.g., the visual design of an ad, consumer demographics, etc.). We further assume that the error terms are: $u_t \sim N(0, H)$ and $v_t \sim N(0,\Omega)$.

Our focus is to examine the effect of perceptual (dis)fluency on consumer ad clicking behaviour. An endogeneity issue arises because a consumer would only click on an ad if she actually noticed and processed the ad while browsing online. We thus take a two-stage approach to model consumer digital ad click-through behaviour following a Heckman procedure (Heckman, 1976). In the first stage, we use a Probit model to estimate the probability that a consumer processed a digital ad. In the second stage, we use a dynamic factor model to estimate consumer click-through behaviours under the impact of the unobservable and time-varying (dis)fluency. To account for the potential sample selection bias, we incorporate in the second stage, the inverse Mills ratio, which is calculated from the first stage results.

Stage one: likelihood of consumer ad processing

Let us denote p_{it} as a binary behaviour of advertisement processing of household *i* at time *t*.

$$p_{it} = 1\, if\ U_{it} > 0 \tag{3.3}$$

$$U_{it} = a_{it} + bX_{it} + cZ_t + \varepsilon_{it} \tag{3.4}$$

where a_{it} is the constant term, the inverse Mill's ratio IMR_{it} is calculated as:

$$IMR_{it} = \frac{\phi(\Omega)}{\Phi(\Omega)} \tag{3.5}$$

where $\Omega = a_{it} + bX_{it} + cZ_t$, ϕ denotes the standard normal probability density function, and Φ denotes the standard normal cumulative density function.

Stage two: consumer ad click-through

We jointly model the number of click-throughs and number of ad impressions per minute as two co-moving time series driven by an underlying latent process, i.e., processing fluency (F). For each household *i* in the dataset, the observation equation is written as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \end{bmatrix} + \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} F_t + \begin{bmatrix} \varphi_1 \\ \varphi_2 \end{bmatrix} IMR_t + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{3.6}$$

where the observed dependent variables are consumer ad impressions and click-through, respectively. *F* stands for fluency, and *IMR* is the inverse mills ratio calculated from Stage one. ϵ is the vector of error terms. λ and φ are parameters.

The transition equation for each household at time *t*, f_t, is expressed in the following form:

$$f_t = \sum_{p=1}^{P} \delta_p f_{t-p} + [\beta_1 \quad \beta_2 \quad \dots \quad \beta_4] \begin{bmatrix} AdS_t \\ AdC_t \\ Br_t \\ Dev_t \end{bmatrix} + u_t \tag{3.7}$$

where δ_p is the parameter of the autoregressive terms (*P* is the highest order of lags). We have incorporated exogenous variables into the transition equation, where *AdS* refers to ad stock, which is measured as the cumulative number of impressions of each type of ads (i.e., finance, travel, and others). *AdC* includes a set of ad creative features, including the dominant color, length of texts, and emotional appeal of an ad. β's are the parameters of exogenous variables. *Br* is a set of variables that measure the cumulative amount of time an individual has spent browsing certain types of online content (i.e., finance, travel, retail, leisure). Dev captures the browsing device being used (i.e., PCs, tablets, or smartphones). β_1 to β_5 are parameters for each of the five exogenous factors, respectively. u_{it} is the error term.

3.6.3 Data

We obtained a unique dataset of ad impression and clicking behaviour of 655 households[15] in the Netherland from 14th October 2016 to 31st March 2017. The dataset consists of a display ad network and nine of its clients from seven B2C industries, including travel, financial service, department stores, holiday villages, printing service, grocery retailer, and education providers. We have in total 122,243 ad impressions and 912 click-throughs (click-through rate of 7.46%). For each ad impression and click, we can obtain the exact time and duration of each impression, together with the device used. As for the ad creative, a rich set of creative-level attributes is accessible. For example, we obtain the type, format (i.e., static vs. transitional), color, text content, and the emotional appeal in each ad creative. Specifically, we obtain the level of joy (i.e., positive appeal) and sorrow (i.e., negative appeal) on a scale from 1 to 7 for each ad creative. Further, we can also access the browsing activities of each household at websites such as major price comparison websites and major competitors of the focal advertisers. Finally, for each household, detailed demographic information is available, such as the size, composition, social status, education, income level, and internet usage level, to name a few.

Given that ad browsing is typically clustered and concentrated over a short period of time and that consumer's perceptions towards ads get updated quickly, we follow Todri et al. (2020) and divide the dataset by minute and measure household behavioural metrics within each minute (e.g., number of ad impressions and clicks per minute). For ad creative level attributes, if multiple ad creatives are viewed within the same minute, we use (1) the relative proportion of impressions or (2) the average level across all impressions to measure the level of exposure to certain creative elements per household. In the prior case, if a consumer was exposed to two ads (i.e., two impressions) during the same minute, and the ads are from a travel and an insurance advertiser, respectively, her exposure to the travel category during this minute should be 0.5 (i.e., 1 divided by 2). In the latter case, if a consumer was exposed to two ads with the level of the positive appeal being 2 and 4, respectively, then her exposure to positive appeal during the minute will be 3 (i.e., the average of 2 and 4).

Table 3.2 gives a summary of the descriptions of the variables used in model analysis. To prepare the dataset for model estimation, we dropped individuals with no click-through at all during the entire data period. Next, given the number of parameters that need to be

[15] In this paper we use "households" and "consumers" interchangeably.

estimated and considering model convergence ability, we dropped individuals with fewer than 50 observations.

The final dataset consists of 80,345 observations (household-minute) of 655 households across 324 unique ad creatives. On average, each household has 123 observations.

Table 3.2 Variable Descriptions

Variables	Descriptions
Creative/Advertiser level attributes	
AdC_positive	Average rating of positive emotional appeal (joy)
AdC_negative	Average level of negative emotional appeal (sorrow)
AdC_blue	% of ads with dominate colour of blue (vs. red)
AdC_green	% of ads with dominate colour of green (vs. red)
AdC_size	Average size (height x width, in pixels) of ads
AdC_textlen	Average lengths of texts (number of characters) in ads
AdC_transitional	% of ads with animations
AdS_retail	Cumulative % of ad impressions from retailing advertisers
AdS_travel	Cumulative % of impressions from travel advertisers
AdS_finance	Cumulative % of impressions from finance advertisers
Ad browsing metrics	
Br_impression	Total number of ad impressions
Br_click	Total number of ad click-throughs
Br_process	Dummy variable indicating ad processing
Br_pc	% of ad impressions using PC (vs. tablet)
Br_phone	% of ad impressions using smartphone (vs. tablet)
Br_time	Total duration (in seconds) of measurable ad viewable time
Web browsing metrics	
Web_travel	Cumulative duration of time spent on browsing travel contents
Web_finance	Cumulative duration of time spent on browsing financial contents
Web_retail	Cumulative duration of time spent on browsing retail contents

Note: all variables, except web browsing and adstock metrics, are measured by minute

3.6.4 Results

Stage One Probit Results

The purpose of the stage one model is to estimate consumers' likelihood of processing display ads using a Probit model. The dependent variable is *Br_process*, a dummy variable that takes the value of one if a consumer processed display ad during a specific minute and zero otherwise. Given that the action of processing is again unobservable from a secondary dataset, we consider processing occurred if any ad was displayed in full during the minute (i.e., positive, measurable viewable time[16]). Table 3.3 and Table 3.4 present summary statistics of ad creative level variables and time-variant variables used in our model, respectively.

Table 3.3 Summary Statistics of Ad Creative Level Variables

Variable	Mean	Std. Dev.	Min	Max
(N=342)				
AdC_red	185.114	70.951	0	255
AdC_green	184.392	64.540	7.198	255
AdC_blue	183.293	71.570	4.728	255
AdC_negative	0.088	0.293	0	2
AdC_positive	0.178	0.762	0	5
AdC_transition	0.684	0.466	0	1
AdC_textlen	600.807	587.635	4	4,042
AdC_size	11.372	0.667	16,000	485,001.828
AdS_travel	0.061	0.240	0	1
AdS_finance	0.187	0.391	0	1
AdS_retail	0.480	0.500	0	1

We estimated a Probit model of consumers' likelihood of processing display ads with household-level fixed effects (see a summary of results in Table 3.5). Specifically, we estimated two models, with and without incorporating emotional appeals (positive and negative) of ads. We find that the model performance (log-likelihood) has significantly improved by including emotional appeals, as indicated by likelihood ratio test results. From Model 2, Table 3.5, we notice that, consistent with what theories suggest, the likelihood of consumers processing display ads increases with their exposures to ads with negative emotional appeals ($b_{AdC_{negative}}$= 0.262, p=0.02), and decreases with exposures to ads with positive appeals ($b_{AdC_{positive}}$= -0.144, p=0.03). Further, we find that consumers are more likely to process ads with shorter texts ($b_{AdC_{textlen}}$= -0.043, p<0.01) and without animations ($b_{AdC_{negative}}$= -0.093, p<0.01). They are also more likely to do so when they are browsing with PCs than with phones ($b_{Br_{pc}}$= 0.945, p<0.01).

[16] https://support.google.com/google-ads/answer/7029393?hl=en-GB

Table 3.4 Summary Statistics of Main Model Variables

Variable (N=80,345)	Mean	Std. Dev.	Min	Max
Br_click	0.011	0.215	0	48
Br_impression	1.521	2.497	1	206
Br_process	0.527	0.499	0	1
Br_time	27,652.810	231760.700	0	46,400,000
AdC_green	180.373	64.325	5	255
AdC_blue	180.212	67.151	2	255
AdC_negative	0.048	0.225	0	3
AdC_positive	0.108	0.604	0	5
AdC_textlen	852.907	1583.218	24	123760
AdC_transition	0.798	0.393	0	1
Web_retail	105.950	1,092.734	0	24,710.610
Web_travel	49.661	829.337	0	17,431.090
Web_finance	51.277	426.030	0	9,625.964
Br_phone	0.016	0.126	0	1
Br_pc	0.878	0.326	0	1
AdS_finance	0.238	0.421	0	1
AdS_retail	0.049	0.214	0	1
AdS_travel	0.459	0.492	0	1

Note: All variables, except for web browsing metrics, are measured by minute

Stage Two DFM Results

The focus of this paper is to quantify processing (dis)fluency during online browsing and uncover its drivers. Given that individuals in our dataset do not observe and interact with each other, we estimate a dynamic factor model for each of the 655 individuals in our dataset separately. In this way, we also account for unobservable individual level heterogeneities.

Since we are interested in the effect of unobservable factor *F* on the number of impressions and clicks (i.e., λ's from Eq.3.6) and the effect of exogenous variables on *F* (β's from Eq.3.7), we summarize these parameter estimates in Table 3.6. Specifically, we present the mean and median levels of parameters across all individuals.

Table 3.6 and Figure 3.8 present the impact of exogenous variables on *F*. Firstly, results show a positive effect of text length (Mean $_{\text{AdC\_textlen}}$ =0.438) and size (Mean $_{\text{AdC\_textlen}}$=0.131) of an ad. Further, ads with animations on average are associated with a higher value of F (Mean $_{\text{AdC\_transition}}$ =1.633, Median $_{\text{AdC\_transition}}$ =0.107) compared with stationary ads. Further, too much exposure, which is measured by the duration of ad viewable time, is positively associated with F ($Mean_{Br\_time}$ = 0.288, $Median_{Br\_time}$ =0.019). Drawing results from the extant literature on the relationship between ad creative elements and consumer processing results described above help us conclude with confidence that F captures the processing disfluency of consumers.

Table 3.5 Study 3—Summary of Probit Results (Stage One)

VARIABLES	Model 1 Process	Model 2 Process
AdC_negative		0.262**
		(0.112)
AdC_positive		-0.144**
		(0.066)
Br_impression	-0.268***	-0.270***
	(0.032)	(0.032)
AdC_green	-0.090***	-0.092***
	(0.032)	(0.032)
AdC_blue	0.020	0.020
	(0.030)	(0.030)
AdC_transition	-0.094***	-0.093***
	(0.021)	(0.021)
AdC_textlen	-0.044***	-0.043***
	(0.013)	(0.013)
Br_phone	-0.140	-0.140
	(0.143)	(0.143)
Br_pc	0.944***	0.945***
	(0.066)	(0.066)
AdS_finance	0.247***	0.250***
	(0.025)	(0.025)
AdS_travel	0.287***	0.289***
	(0.045)	(0.045)
AdS_retail	0.046**	0.045**
	(0.022)	(0.022)
Observations	80,345	80,345
Number of households	655	655
Log Likelihood	-48,537.24	48,526.382
LR test	$\chi^2(2)$=5.51**	

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

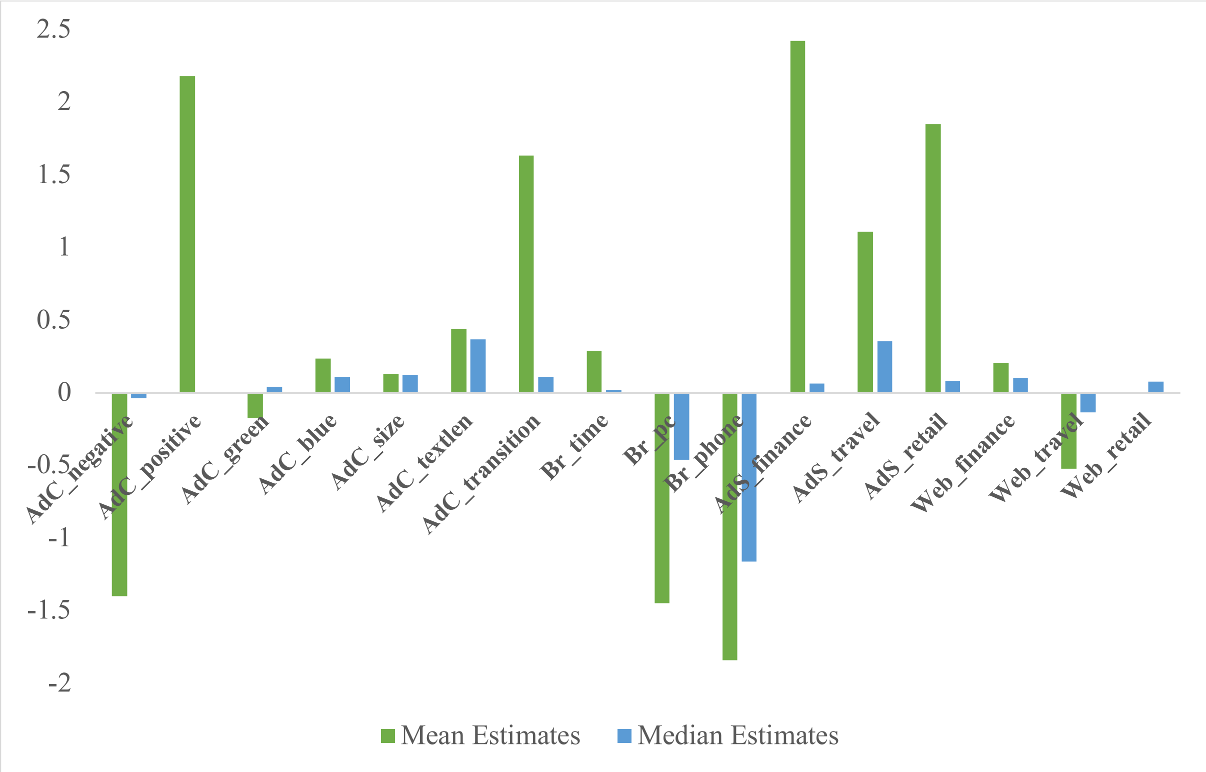
More importantly, we find that a negative effect of positive emotional appeal in ad creative ($Mean_{AdC\_positive}$ =-1.398, $Median_{AdC\_positive}$ =-0.035), and a positive effect of negative emotional appeal ($Mean_{AdC\_negative}$ =2.183, $Median_{AdC\_negative}$ = 0.007). Therefore, we find results resonating with those in Study 1 and 2 and our hypotheses so that negative ad emotional appeal leads to consumer processing disfluency. Further, *F*'s positive impact on the number of click-throughs is consistent with our experimental results and H2b that disfluency leads to higher clicking. Using data collected from the field, Study 3 shows robust empirical evidence supporting H1 and H2b.

Table 3.6 Study 3—Summary of DFM Results (Stage Two)

Variables	Mean Estimates	Median Estimates
Effect on F (β's)		
AdC_negative	-1.398	-0.035
AdC_positive	2.183	0.007
AdC_green	-0.172	0.042
AdC_blue	0.235	0.109
AdC_size	0.131	0.122
AdC_textlen	0.438	0.369
AdC_transition	1.633	0.107
Br_time	0.288	0.019
Br_pc	-1.446	-0.458
Br_phone	-1.840	-1.163
AdS_finance	2.426	0.067
AdS_travel	1.108	0.354
AdS_retail	1.849	0.084
Web_finance	0.206	0.104
Web_travel	-0.521	-0.132
Web_retail	0.003	0.079
Effect on Click		
IMR (φ_1)	0.500	0.047
F (λ_1)	0.027	0.017
Lag. F (δ_1)	0.071	0.042

Finally, it is interesting to notice from the results in Table 3.6 that more time spent in content browsing at travel websites, in contrast to that at retail and finance websites, generate a lower (higher) level of disfluency (fluency) of consumers. Ads with green as the dominant color are more fluent to process than those with red and blue as the dominant color. Finally, the positive estimates of *IMR* indicate a positive association between the likelihood of ad processing and ad clicking.

Figure 3.8 Study 3—Summary of DFM Results



3.7 Discussions

Our research highlights the importance of processing disfluency as an effective mechanism leading to consumer clicking in online display ads context. Following the growing body of research on how different stimuli influence the attitudes and judgments of audiences through processing fluency (Alter and Oppenheimer, 2009; Chae and Hoegg, 2013; Landwehr et al., 2011), we demonstrate that negative emotional appeals such as fear and sorrow of an online display ad cause more consumer attention and cognitive effort, leading to a higher level of disfluency. We further find that processing disfluency can lead to higher consumer willingness to click because it ignites consumer interests and exploration of alternatives (Graf and Landwehr, 2015; Walter et al., 2020). We found support for our conceptual framework and propositions (see Figure 3.1) using a multi-study/method approach.

Specifically, Study 1 used an experimental approach to demonstrate the disfluency-based mechanism underlying the effects of negative ad appeal on consumers' willingness to click, while Study 2 replicated the findings of Study 1 using another product/service category and explored the moderating effect of utilitarian vs. hedonic goods on the effect of negative ad appeal on disfluency. Finally, Study 3 validated our experimental findings using field data to show the impact of negative ad appeal on consumer ad clicking through processing disfluency.

The findings in this study are not only limited to the context of online display ads; in fact, they can be applied to most types of advertisements whose aim is to capture consumer attention and elicit their interests. We investigate the impact of negative (vs. positive) emotional appeal of digital ads on consumer processing disfluency and in turn ad clicking. Hence our focus is not on the context (i.e., digital display ads); instead, it is on the engagement tactics adopted by advertisers to grab consumer attention to an appropriate extent. In this way, consumers are not annoyed but their attention is shifted from the major task (e.g., content browsing) to the ad.

Contributions and implications

We contribute to the literature in three major ways. We first contribute to the digital advertising literature by investigating processing disfluency as a critical factor influencing consumer ad clicking decisions. We study the emotional appeal of display ads as an antecedent of processing disfluency, a metacognition that refers to the level of ease of processing a certain stimulus (Graf et al., 2017). Recognizing its importance in influencing people's judgements and attitudes, previous research has uncovered quite a few antecedents of processing fluency, including linguistic, visual, and olfactory stimulus, to name a few (Alter and Oppenheimer, 2011; Mahmood et al., 2019). Drawing on affect-cognition theories (Matovic et al., 2014), we find that negative emotional appeal takes more attention and cognitive efforts of consumers to process an ad, leading to a higher level of processing disfluency.

Secondly, we contribute to the literature by discovering the consequence of processing disfluency in the context of online display ads. While extant studies mostly advocate the positive impact of processing fluency on consumer attitudes and judgements in retail, entrepreneurial marketing, and advertising settings, some more recent research has started to shed light on the positive impact of disfluency. We find that processing disfluency of display ads induced by negative emotional appeals leads to a higher willingness to click and more positive attitudes towards the ad. However, processing disfluency leads to a more negative attitude towards the brand. In this way, we contribute to the literature by highlighting the trade-off between consumers' reactions and attitudes to the ad against attitudes towards the brand.

Finally, another contribution of our paper lies in applying the dynamic factor model in the field of marketing, or more specifically, advertising research. The dynamic factor model has been mostly used by finance and economics scholars to study the stock market dynamics or macroeconomic cycles (Kokszka et al., 2015; Ng et al., 1992). In contrast, there has been little research in marketing that adopts DFM. Nevertheless, DFM is suitable to address several modelling challenges in marketing research, especially research on consumer behaviours under the impact of unobservable factors. For example, DFM can model an unobservable construct (i.e., disfluency) as a dynamic term that varies over time and incorporate it as an intermediate factor between observable ad emotional appeal and consumer ad clicking behaviours.

Our study also has practical contributions to digital marketers. Our findings address the positive impact of processing disfluency on consumer ad clicking and purchase intention and ad liking. We particularly highlight that while negative ad appeals cause disfluency by creating certain disruptions along with consumers' browsing experience, they do not evoke ad annoyance, which easily backfires and frustrates consumers (Edwards et al., 2002). Practitioners can use such "healthy" disfluency to shift consumer attention from the web contents to the ad (Bell and Buchner, 2018). Despite the positive effects of disfluency, our results also show its negative impact on consumer brand attitude. When designing digital display ads, marketers are recommended to carefully evaluate the cost and benefit of inducing processing disfluency through ad creative elements and engagement tactics. More specifically, marketers may use negative ad appeal to shift consumers' attention and prompt their ad clicking and potentially product/service purchases. However, such short-term gain may be at the expense of long-term brand equity and revenues.

Finally, our results indicate that the product or service category makes a difference so that the effect of negative emotional appeal on processing disfluency and then on consumer ad clicking is stronger for utilitarian than hedonic goods. Therefore, marketers of utilitarian brands should consider using disfluency-induced ad clicking more, but should be more cautious of the trade-off between short- and long-term benefits of the brand.

3.7 Limitations and future research

This research is subject to several limitations. Firstly, while we have access to a very detailed and comprehensive field dataset, we do not have information regarding the website where each ad is displayed. Consequently, we are not able to incorporate the matching between the contents of the ad and the website into our empirical model. Previous research has identified ad matching as a critical factor influencing consumer attitudes towards an ad (Goldfarb and Tucker, 2011).

Secondly, we only have access to advertisers from the finance, travel, retail, and print industries. However, consumers are exposed to a mass number of display ads from a large variety of advertisers. Therefore, we are not able to capture the full online journey of consumers in our dataset. Although such data limitation does not significantly influence the findings of our study, future studies would benefit from having a richer dataset to draw more robust conclusions regarding the linkage between ad appeal, processing fluency, and ad clicking behaviours.

Thirdly, emerging types of digital ads such as native ads have been rising fast. The purpose of such ads is not to "disturb" consumer browsing and shift their attention. Instead, it is to keep consumers' browsing as smooth as possible so that they do not realize the existence of advertised contents. Future research may shed more light on these ads.

Finally, the focus of this paper is to study processing disfluency induced by the emotional appeal of online display ads. Unlike TV ads, online display ads are typically placed alongside web content that consumers browse. However, in our experimental studies, we have only created display ads as stimuli without having a fictitious webpage. Therefore, we might have over-estimated the effect of ad emotional appeal on consumer processing disfluency since consumers may not notice the display ads at all in real settings. Future research would be more rigorous to simulate the real online browsing scenario for consumers.

3.8 Conclusion

While digital display advertising has become a business worth hundreds of billions of USD, how to effectively engage with consumers and induce them to click remains an open question. This paper anchors at processing fluency theories and affect-cognition theories and finds that negative ad emotional appeals induce processing disfluency, which surprisingly leads to more ad clicking of consumers. While marketers endeavor to develop new display advertising tactics like native ads (i.e., ads that look like the surrounding non-sponsored contents) that generate a minimal level of disruption (e.g., Aribarg and Schwartz, 2020; Wang et al., 2019), our findings shed light on an alternative route. Marketers may consider creating a "spark" in consumers' browsing experience by inducing processing disfluency so that consumers are stimulated but unannoyed, hence not causing a backfire.

CHAPTER 4

Essay 3: The Evolution of Equity Crowdfunding: Insights from Co-investments of Angels and the Crowd

Abstract

Equity crowdfunding platforms are at the center of the digital transformation of early-stage venture funding. These digital platforms were originally heralded as a democratizing force in early-stage finance due to their role in facilitating the exchange between entrepreneurs and a multitude of non-professional small investors ("the crowd"). Equity crowdfunding platforms have experienced considerable growth and now attract professional investors, including business angels. The presence of angels alongside the crowd on equity crowdfunding platforms has raised questions about whether these digital platforms can continue to play their role in democratizing access to capital. Using data from a leading equity crowdfunding platform, we examine the interplay between the investment decisions of angels and the crowd. We find evidence of information flows in crowdfunding platforms between angels and from angels to the crowd. We find angels play an important role in the funding of large ventures, whereas the crowd fill not only the funding gaps for such large ventures but also plays a pivotal role in the funding of small ones. The complementarity between angels and crowd investors seems to increase the overall efficiency in an otherwise highly asymmetric and uncertain market, confirming that digitization can indeed bring important benefits to venture investment.

4.1 Introduction

Raising finance is one of the most challenging aspects of entrepreneurship (Lee et al., 2015). Direct investments into start-up businesses, the majority of which are likely to fail, are high-risk, and start-up entrepreneurs often have limited access to traditional sources of financing.

The financial crash of 2008 created additional barriers to early-stage funding, which in turn gave impetus to regulators in the United Kingdom (UK) to facilitate access to capital for early-stage ventures (Mollick and Robb, 2016). Regulators actively supported fintech start-ups with the goal to reduce the dominance of institutional investors (Hernando, 2016).

As a result, the Financial Conduct Authority (FCA) has adopted a light-touch approach towards Equity Crowdfunding (ECF) regulations in the UK (Vulkan et al., 2016). In addition, to encourage the public to invest in start-ups, the UK government offered generous tax incentives through the Seed Enterprise Investment Scheme (SEIS) and the Enterprise Investment Scheme (EIS). With these incentives in place and their simple-to-use digital interface enabling easy-to-access venture information, ECF platforms quickly gained popularity among the public. These digital platforms, which differ significantly from traditional sources of financing, have increased optimism regarding the future of start-up finance, with ECF raising 1,130 million USD in funding in the UK alone (Statista, 2018), and is now the second-largest investment category in the UK (by the number of companies funded) after venture capitalists (Beauhurst, 2017).

ECF platforms not only attract non-professional small investors ("the crowd") but also attract angel investors and venture capitalists (VC) interested in diversification or convenience. As such, ECF platforms provide a wide range of potentially high-return early-stage ventures with the opportunity to spread risk across multiple ventures and limited administrative burden for investors seeking passive investments (AIG, 2016; Landström and Mason, 2016).

Beyond the convenience, digital ECF platforms also provide entrepreneurs the ability to use media such as video and images to provide campaign information and to post real-time updates to signal venture quality. However, information asymmetry still presents a challenge on crowdfunding platforms (Ahlers et al., 2015), and finding the right balance between facilitating fundraising for new ventures and protecting non-professional investors from ill-advised decisions and even financial ruin is non-trivial.

In this respect, some argue that professional and angel investors can play an important signaling role on these platforms (Agrawal et al., 2016), making the increasing presence of angels and VCs on ECF platforms a positive development (BBB & UKBAA, 2017; Mason and Botelho, 2014). Leading ECF platforms such as Crowdcube and CircleUp actively encourage co-investment between the crowd and large investors (TechCrunch, 2016). On the other hand, some commentators argue that large investors will eventually dominate these platforms and weaken the democratizing purpose of these new financing channels (Zhang et al., 2015). However, the impact of large investors such as angels on ECF is yet unclear and, to the best of our knowledge, prior research has not studied how angels and crowd investors interact on digital crowdfunding platforms.

The evolution of ECF platforms can have long-lasting repercussions for the funding of early-stage ventures in terms of the types of ventures being funded, the way in which entrepreneurs pitch campaigns, and the nature of innovation (Zhang et al., 2015). It is, therefore, imperative to determine how angels and crowd investors interact on these digital platforms. Are angels "crowding out" crowd investors, or can angels help reduce information asymmetries by providing valuable and informative signals to the crowd? If angels dominate the platforms, the digitization would only benefit large investors and perpetuate funding imbalances associated with conventional funding.

We seek to address these questions by analyzing one of the UK's leading ECF platforms from July 2012 until August 2017. Over this period, we observe an increasing trend in terms of both volume and fundraising success of large ventures with a funding goal higher than £100,000 on the platform (ventures raising funding are called "campaigns," and we use these terms interchangeably). We also notice an increase in the volume and value of investments by large investors who correspond to the top 1% in terms of the total amount invested and are behaviourally similar to business angels. Despite the growth in the number of large ventures and angel investors, we observe that crowd investors not only complement angels in large campaigns but also play a significant role in funding small campaigns that might not generate sufficient interest from angels. Hence, the fear that ECF platforms will evolve into digital marketplaces dominated by entrepreneurs with large funding needs and large investors such as angels who can fund these needs seems unfounded. ECF platforms seem to have retained their democratic structure, and the fast-paced flows of information between diverse investors on these dynamic digital platforms have facilitated access to capital for both small and large ventures, previously unserved by traditional offline sources of finance.

To study the co-investment behaviour of angels and crowd investors, we employ the theoretical lens of signaling theory (Connelly et al., 2011, for a review). We propose and demonstrate that high-contribution pledges (i.e., pledges contributing a high percentage to a campaign's funding goal) serve as an effective investor-generated signal of venture quality because they are costly and difficult to imitate. In addition, we propose and show that angel investments are more informative compared to crowd investments. We further show that perceived similarity between signal recipient and sender enhances information flow resulting in angels (compared to crowd investors) reacting more positively to high-contribution pledges from other angels. However, the size of the venture moderates this effect, suggesting that the effectiveness of angel-generated signals depends on the funding context.

Our results show that ECF investors rely on high-contribution pledges in general and on angel pledges in particular to inform their funding decisions. In light of the signaling role played by angel pledges, regulators ought to focus on further incentivizing and facilitating information flow that reduces market frictions while protecting crowd investors from being misled (FCA, 2018). Considering the impersonal nature of digital crowdfunding, information asymmetry, and the risks for inexperienced investors, there is a need to enhance standardized regulations on investor information disclosure, platform due-diligence, and explicit investor categorization. Such regulatory measures would increase transparency and facilitate information flow, further enhancing the benefits and efficiency gains from the digitization of early-stage finance.

4.2 Literature Review and Hypotheses

4.2.1 Angel investors in ECF

Angels are generally defined as "high net worth individuals who invest their own money, either alone or with others, directly in unquoted businesses in which there is no family connection" (Mason et al., 2016, p.322). Angels are a diverse group (Drover et al., 2017; Wright et al., 2015) that varies on demographical and behavioural dimensions (Sørheim and Botelho, 2016). While most angels make individual investment decisions, other angels invest via "angel networks" comparable to investor-led ECF platforms (e.g., Angel's Den, Syndicate Room) where investors pledge by following a lead investor (Agrawal et al., 2016). Other investors invest via informal offline investment networks and recently via online company-led ECF platforms like the one we study.

Angels usually concentrate their investments in specific markets or sectors to leverage their experience and expertise (Maula et al., 2005; Wright and Westhead, 1998). However, there is also evidence that angels diversify their investments, with some angels holding a portfolio of more than 20 different ventures at a time (BBB and UKBAA, 2017). In addition, whereas angels have traditionally maintained personal contact with entrepreneurs (Mason and Botelho, 2014; Sørheim and Botelho, 2016), some angels are more hands-off with limited interest in managerial support (e.g., Erikson et al., 2003; Sørheim and Landström, 2001). Further, micro-lending and crowdfunding platforms have gained popularity among younger and less experienced angels seeking convenience (Wright et al., 2015) and even hands-on angels who are willing to hold passive investments (Landström and Mason, 2016). Hence, ECF platforms are likely most attractive to angels seeking diverse ventures and convenience. These investors can, in turn, influence the investment dynamics on these digital platforms by providing signals to other investors.

4.2.2 Investor generated signals in ECF

ECF is characterized by high uncertainty due to the information asymmetry between entrepreneurs and investors, the short fundraising time frames (30 to 60 days), the early stage of ventures, and limited offline contact with entrepreneurs. In this context, signals of venture quality (i.e., informative cues of the venture's ability to earn a positive cash flow) as proposed by signaling theory gain importance (Vismara, 2016a).

Previous research has identified several campaign-level attributes, such as share of equity offered and entrepreneurs' social, human, and intellectual capital as effective signals (Ahlers et al., 2015; Vismara, 2016a). Similarly, communication with investors (Block et al., 2018), narrative style (Parhankangas and Renko, 2017), and visual cues (Mahmood et al., 2018) are used by entrepreneurs as signals of venture quality. In addition, signals from sources other than entrepreneurs can disambiguate the effect of several entrepreneur-generated signals (Plummer et al., 2016). For instance, third-party signals such as endorsements from angels and VCs and the investment decisions by other investors have been found to influence start-up success (Kuppuswamy and Bayus, 2017).

According to signaling theory, an effective signal is costly, difficult to replicate, and contains private information (Spence, 1973). A high-contribution pledge in a specific venture can convey the investor's confidence in the venture and, if costly to replicate, can serve as an effective signal of venture quality to other investors. ECF platforms often list previous pledges for a specific venture in descending order by value; these digital platforms thus facilitate inter-investor signaling by giving more visibility to large pledges. Not surprisingly, recent crowdfunding studies find that large investments in a venture influence subsequent investors (Burtch et al., 2013). Consequently, large investments from early funders result in a higher likelihood of campaign success (Burtch et al., 2013; Vismara, 2016b). While the signaling impact of large investments on subsequent investors' behaviours has been extensively examined by extant corporate finance and private equity literature, it has not been confirmed in the context of equity crowdfunding. Therefore, we hypothesize:

***H1**: High-contribution pledges in a campaign positively influence the subsequent amount pledged by investors in the same campaign.*

4.2.3 Identity of signal sender

Bernstein et al. (2016) note that investors may focus more on the identity of previous investors to assess venture quality in markets with information asymmetry. Hence, we propose that the identity of the investor generating the high-contribution pledge is likely to influence how investors interpret investment signals.

Previous literature on signaling and information exchange stresses the differing credibility and trustworthiness of signals depending on their source (e.g., Gomulya and Mishina, 2017; Kang and Herr, 2006). For instance, observable endorsements from experts have been found to be effective signals of venture quality (Courtney et al., 2017; Kim and Viswanathan, 2018). Similarly, investors' pledges can be seen as endorsements as they reflect the investors' commitment towards the venture. Given the large distinction in wealth, expertise, and experience between angels and crowd investors (Hornuf and Schwienbacher, 2016), investments from angels will be deemed more informative and will thus be more influential in generating subsequent pledges for a venture. Further, angel investments are associated with higher survival and growth rate of ventures (Kerr et al., 2011) and help attract VCs and other institutional investors (Wallmeroth et al., 2018). We therefore hypothesize:

***H2**: High-contribution pledges made by angels in a campaign have a greater influence on the subsequent amount pledged by investors in the same campaign, compared to high contribution pledges made by crowd investors.*

4.2.4 Identity of signal recipient

Beyond the importance of the signal source, signal decoding may also play an important role. However, decoding signals is susceptible to the characteristics of the recipient (Connelly et al., 2011). Information exchange theories suggest that individuals perceive information delivered by those similar to themselves as more useful (Brack and Benkenstein, 2012). Social proximity, or perceived similarity between individuals, that is "the degree to which people who interact are similar in beliefs, education, social status" (Rogers and Bhowmik, 1970, p.525) could explain these effects (Cowgill et al., 2009). Prior research shows that crowdfunders from similar social categories are more likely to build connections (Greenberg and Mollick, 2017). Therefore, due to perceived similarity, a high-contribution pledge from an angel is likely to have a greater impact on other angels. Therefore, we hypothesize:

H3*: High-contribution pledges by angels in a campaign will have a greater positive effect on the subsequent amount pledged by other angel investors in the same campaign, compared to high-contribution pledges by crowd investors.*

4.2.5 Signal context

Signaling theory identifies costliness and ease of replication as key criteria for signal effectiveness (Spence, 1973). High-contribution pledges in campaigns with a large funding goal (large campaigns) are significantly larger in monetary value than those in campaigns with a small funding goal (small campaigns). They are consequently more difficult to imitate and have higher opportunity costs (Connelly et al., 2011). Moreover, large campaigns are subject to higher materialization risk, as they are less likely to meet the funding goal compared to small campaigns (Belleflamme et al., 2013; Mollick, 2014). Because investment riskiness positively moderates people's willingness to refer to opinions of others with similar sentiments (Gu et al., 2014), we expect the positive impact of high-contribution pledges made by angel investors to be higher in large campaigns than in small campaigns. Our final hypotheses are:

H4a*: Compared to small campaigns, high-contribution pledges by angels in large campaigns have a greater positive effect on the subsequent amount pledged by other angel investors in those same campaigns.*

H4b*: Compared to small campaigns, high-contribution pledges by angels in large campaigns have a greater positive effect on the subsequent amount pledged by crowd investors in those same campaigns.*

4.3 Data

We study investor behaviour using investment data for 50,999 unique investors and 1,151 unique campaigns from July 2012 to August 2017 on one of the UK's leading ECF platforms.[17] The platform we study acts as the nominee of the participating investors, facilitating future funding rounds, and preventing share dilution. It is also similar to other major ECF platforms (e.g., Crowdcube) in terms of size, type, number of deals completed on the platform, and fee

[17] A Non-Disclosure Agreement prevents us from disclosing the identity of the platform.

structure. It has successfully attracted ventures across 13 sectors, with the most popular being financial services, food & drink, digital media, entertainment, and technology.

The platform attracts a large number of diverse investors, ranging from non-professional small investors (typically denominated "the crowd") to sophisticated and high-net-worth individuals. Because investors use multiple platforms, the leading ECF platforms tend to have a similar profile of users.[18] After the public launch of a campaign on the platform, entrepreneurs have 60 days to raise (at least) 100% of the funding goal. If a campaign does not reach its goal, it is deemed unsuccessful, and the venture will not be funded (pledges are returned to investors). Campaigns can reach more than 100% of the funding goal (overfunding is allowed), and prior to the public launch, entrepreneurs can use the platform to raise funds privately (i.e., private launch). Besides basic campaign-level attributes such as funding goal, equity offered, and founding team profiles, a list of prior investors ranked by amount of investments is always displayed at each campaign webpage. Investors are then able to browse and investigate the composition of investors who have already made pledges.

4.3.1 Campaign size

There is considerable variation in the size (funding goal) of the 1,151 campaigns: the average funding goal is £197,821 with a standard deviation of £317,633. We conduct a median split of campaigns with respect to their size and classify campaigns with a funding goal higher than £100,000 as *large campaigns* and all others as *small campaigns*. Table 4.1 summarizes campaign-level attributes by campaign size.

Table 4.1 Average Campaign Attributes by Campaign Size

	Large Campaigns (*N*=640)	**Small Campaigns** (*N*=511)
Pre-money Valuation (£`000)	4,429.28	922.61
Funding Goal (£`000)	315.88	49.96
Campaign Equity Offered (%)	12.54	10.46
Number of Investors	153.25	55.52
Final Funded Rate	0.88	1.09

4.3.2 Investor categorization

We also observe heterogeneity among investors in terms of portfolio size (from 1 to 696 campaigns per investor) and total investment on the platform (from as low as £10 to £14.4

[18] The CEO of the platform notes: *"... platforms (at least the major ones) certainly compete with each other for deals; we also compete for investors, although many investors use multiple platforms."*

million). More importantly, the CEO of the platform confirmed the presence of angels alongside crowd investors. Although we cannot confirm the identity of each angel on the platform, we posit that as long as the behaviour of these investors is similar to the behaviour reported in previous angel investor studies, it is likely that they will be perceived as business angels by other investors (Lee and Thorson, 2008). Hence, we classify the top 1% of investors in terms of the total amount pledged as *angel investors* (*N*=510) and the remaining as *crowd investors* (*N*=50,489).

Our analysis reveals that the minimum total amount a single angel investor invested during the period of our study is £66,000 (although the amount per pledge could be substantially lower). In addition, the behaviour of these investors appears similar to that of UK business angels outlined in recent surveys (BBB and UKBAA, 2017). Table 4.2a presents a comparison of several key metrics, including the median investment value per investor, investors' location, the percentage invested in specific sectors, and the size of the investors' portfolios. As we can see from the table, the angel investors we identified are very similar to those in previous studies.

Table 4.2a Comparison of Angel Behavioural Metrics

	BBB & UKBAA (2017)*	**Current Study**
Median Value of Investments (£)	45,000	80,000
Median Number of Investments Made	2	1
Percentage Invested in 1-5 Companies	79%	83%
Percentage Invested in 10+ Companies	7%	6%
Percentage Located in London	35%	40%
Percentage Invested in ICT/Digital Tech Sector	81%	82%

**All figures obtained and calculated from angel investment metrics in 2016 as reported by BBB&UKBAA*

We also randomly selected a sample of 153 investors we classified as angels (i.e., top 1% of investors) and reviewed in detail their LinkedIn and Crunchbase profiles. By combining the information from the two sources, we find that at least 135 (88%) of investors we classified as angels also qualified as angels based on the criteria that previous research typically uses to profile angels (e.g., UKBAA, 2018).[19] Some of the investors could not be uniquely identified, either because there were multiple investors with the same name or because some investors had

[19] We checked whether an investor met at least one of the following criteria to be classified as angel: (1) having successfully founded start-ups, (2) having taken any chief executive level roles in companies that they do not own, (3) claiming oneself as a professional/angel investor, and (4) being a fund, a syndicate, or an investment organization.

limited profile information. However, being able to link 88% of our sample to open public profiles of angel investors provides reasonable assurance that our classification is robust.

Because we identify angel investors based on their total amount pledged, our approach could account for angels who make few but very large pledges and angels who make a larger number of smaller pledges. In line with existing research on angel behaviour (Landström and Mason, 2016; Sørheim and Botelho, 2016; Wallmeroth et al., 2018), we observe significant heterogeneity among the identified angels. About 3% of angels invested more than one million GBP in a single pledge, whereas 28% made single pledges below £100 (these accounted for a very small percentage of their entire investments). In addition, although 61% of identified angels made fewer than five pledges during the entire period, 5% of angels made more than 90.

We also observe differences in the timing of investment among angels, with some angels investing only during the private launch and others only during the public launch. According to the platform CEO, entrepreneurs often "soft circle part of their round through offline angels" before the public launch. Angels who invest during the private period through offline contacts are likely to treat ECF as an asset class similar to traditional offline investments, maintaining a direct relationship with entrepreneurs and being hands-on. However, investors who invest during the public launch period may consider ECF to be a different asset class, favoring the convenience and hands-off nature of ECF.

Table 4.2b Comparison of Private- and Public-Only Angels

(mean values reported)	**Private-Only Angels** (*N*=82)	**Public-Only Angels** (*N*=168)	***p-value****
Total Amount Invested (£)	253,276	387,141	0.34
Average Amount Invested per Campaign (£)	117,370	146,937	0.25
Number of Campaigns Invested	1.99	1.43	0.24
Percentage of Investments in Large Campaigns	0.94	0.95	0.73
Average Percentage Contribution per Pledge	0.22	0.30	0.08

**p-value for two-sample t-test comparing Private-Only and Public-Only Angels*

In our dataset, we identified those angels who only made pledges during the private launch period (82 angels satisfy this condition) and those who only made investments during the public launch period (168 angels). Angels who only invest during the private launch period likely reveal a preference for an offline connection with entrepreneurs. However, in terms of investment behaviour, we found no significant difference in the average amount pledged (£117,370 vs. £146,937, *p-value* = 0.25), the number of campaigns invested in, preference for small versus large campaigns, and total amount invested (see, Table 4.2b). Hence, although angels may differ in their preference for involvement in ventures (Sørheim and Botelho, 2016), the investment behaviour on the ECF platform is still similar. In contrast, we observe significant differences between the investment behaviour of angels and that of crowd investors (see Table 4.3). For instance, in large campaigns, angels make approximately six times the number of pledges of crowd investors and pledge around 121 times the amount of crowd investors. These results provide further assurance that our strategy for angel identification is robust, identifies hands-on and hands-off angels, and distinguishes angel investors from non-professional small investors.

Table 4.3 Average Investor Level Metrics by Type

	Angel Investors (*N*=510)	**Crowd Investors** (*N*=50,489)
Total Amount Pledged (£)	254,707	2,110
Total Amount Pledged to Large Campaigns (£)	239,783	1,831
Average Amount Invested per Campaign (£)	142,862	1,401
Number of Pledges Made	18	3
Number of Pledges Made to Large Campaigns	13	2
Number of Campaigns Invested	11	2
Number of Days since Registration with the Platform	362	89

4.3.3 Evolution of the platform

Since its inception, the platform has registered an increase in both the value and number of pledges. Figures 4.1 and **4.**2 present the monthly total amount pledged and the monthly number of pledges between July 2012 and August 2017. Splitting the data by campaign size (Figures 4.3 and 4.4), we note a strong increase in the number and success rate of large campaigns over time. We also observe growth in the number of angels joining the platform and the value of angel pledges, with the number and amount pledged by crowd investors remaining stable (Figures 4.5 and 4.6). The simultaneous growth in large investors and large campaigns on the platform could support the arguments of those who claim the participation of angels and large investors on ECF platforms poses a risk to the democratizing role of digitization in early-stage finance. However, the increasing presence of angels is not enough to provide a conclusive answer. One also needs to study angel influence to determine whether angels have achieved a position of dominance. To this end, an analysis of campaign dynamics provides further insights.

Figure 4.1 Monthly Amount Pledged by All Investors

(July 2012 to August 2017)

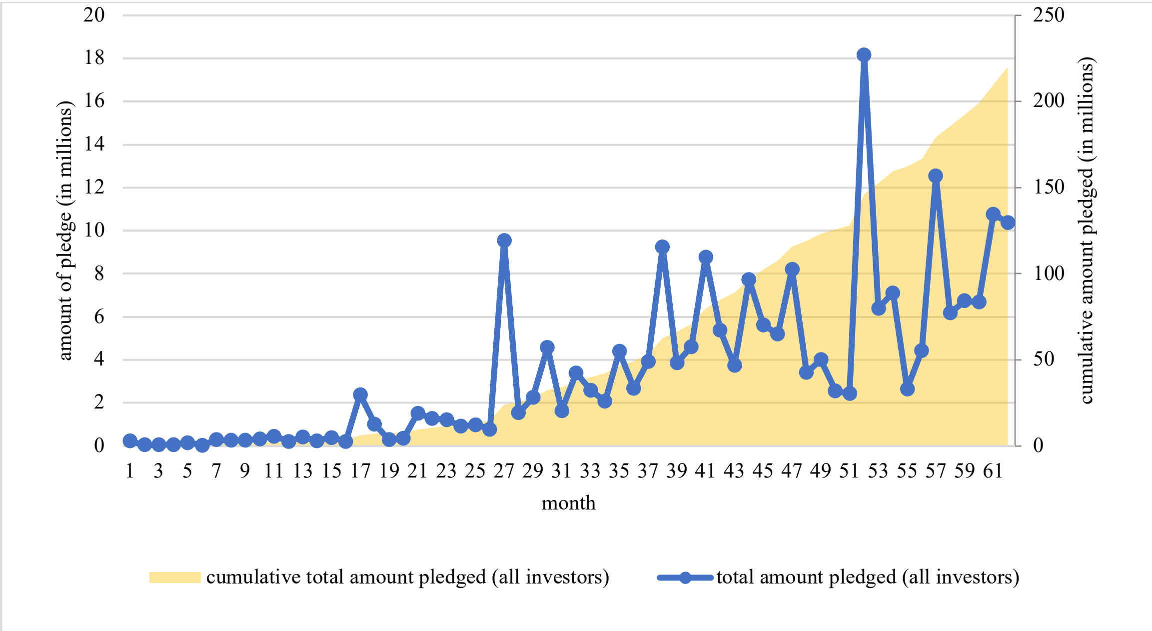


Figure 4.2 Monthly Number of Pledges by All Investors

(July 2012 to August 2017)

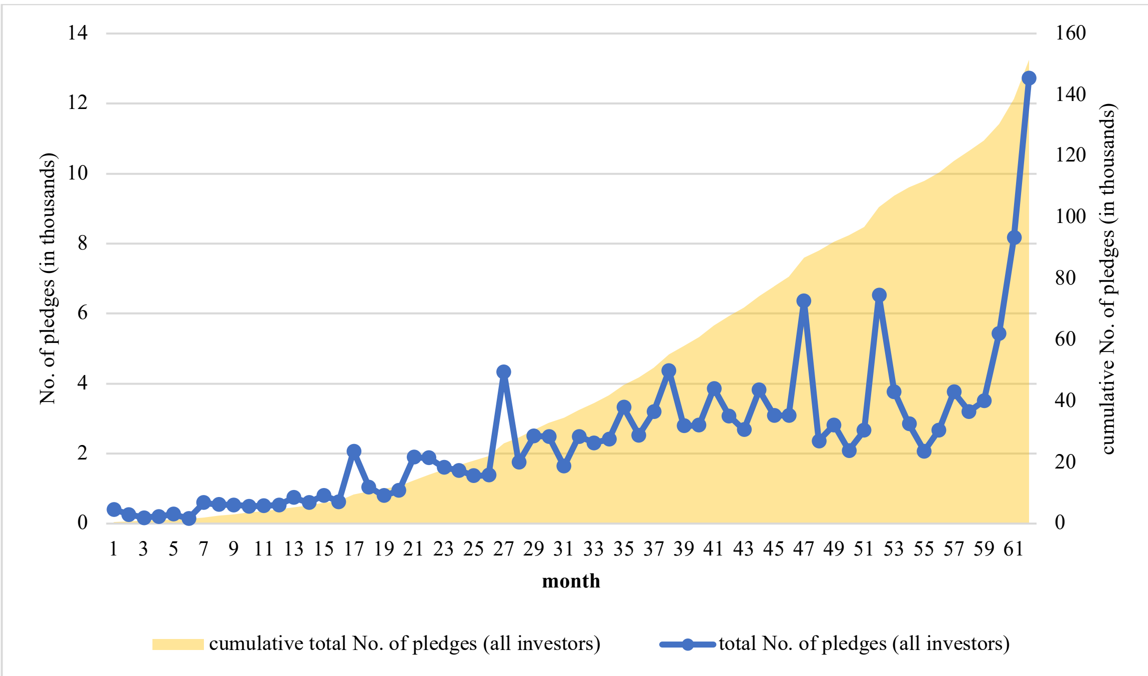


Figure 4.3 Monthly Number of Newly Added Campaigns by Size with Fitted Trends

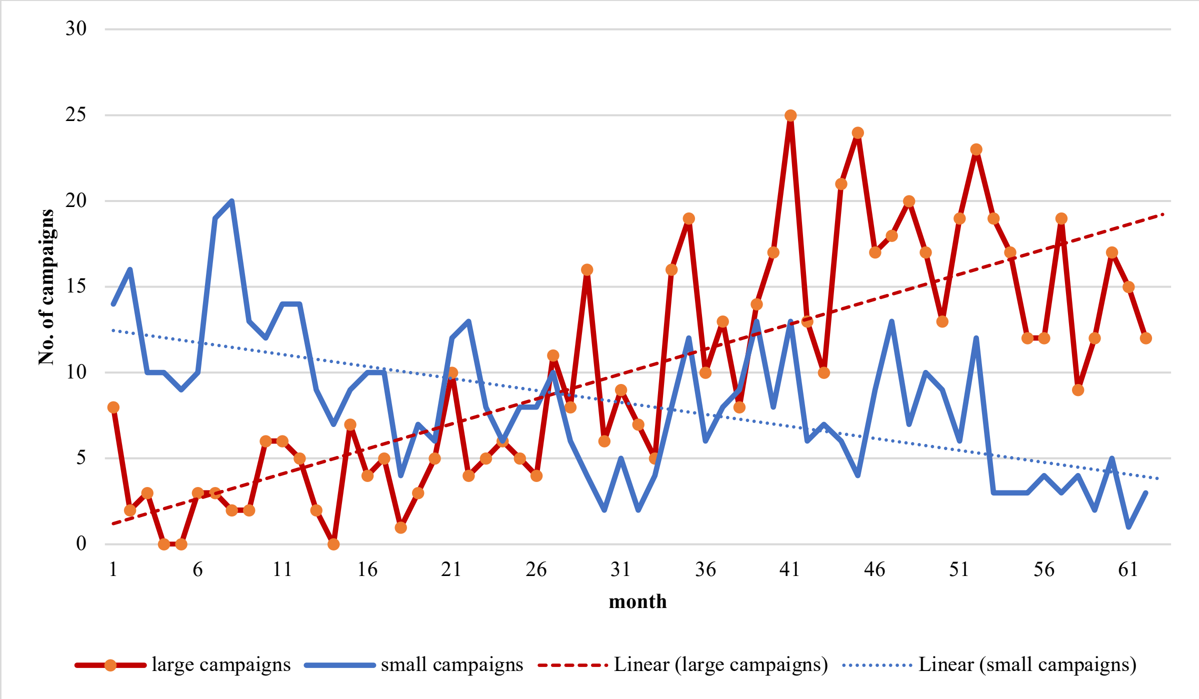


Figure 4.4 Monthly Number of Successful Campaigns by Size with Fitted Trends

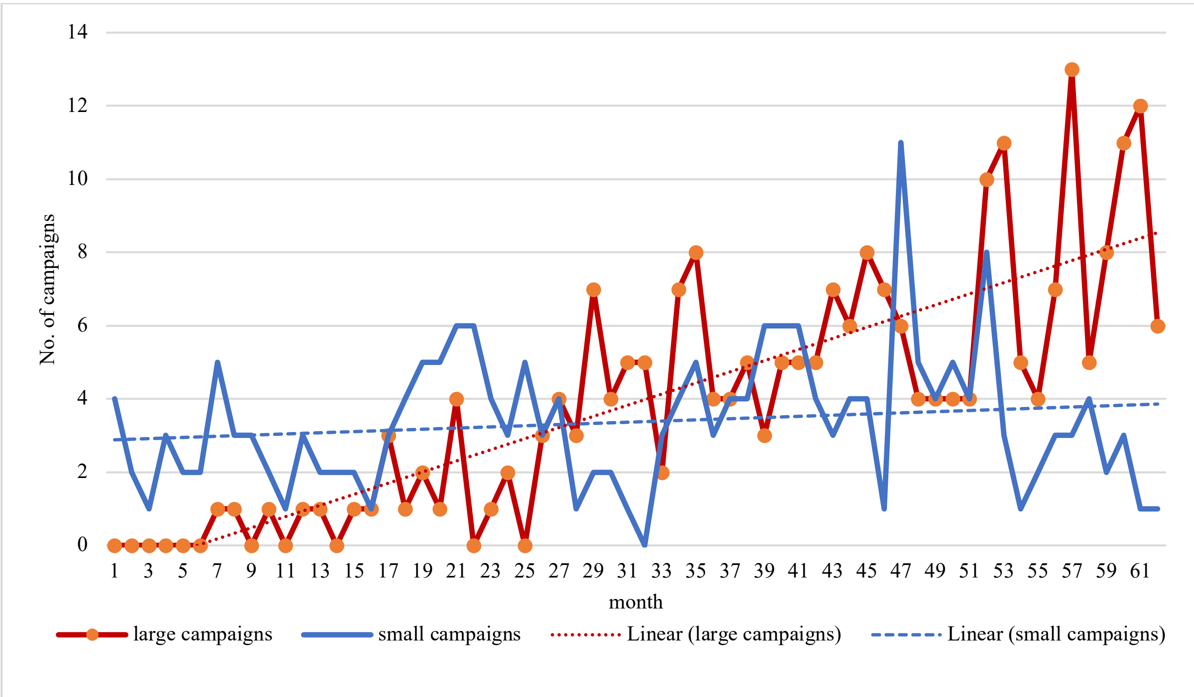


Figure 4.5 Number of Newly Joined Investors by Type and Month with Fitted Trends

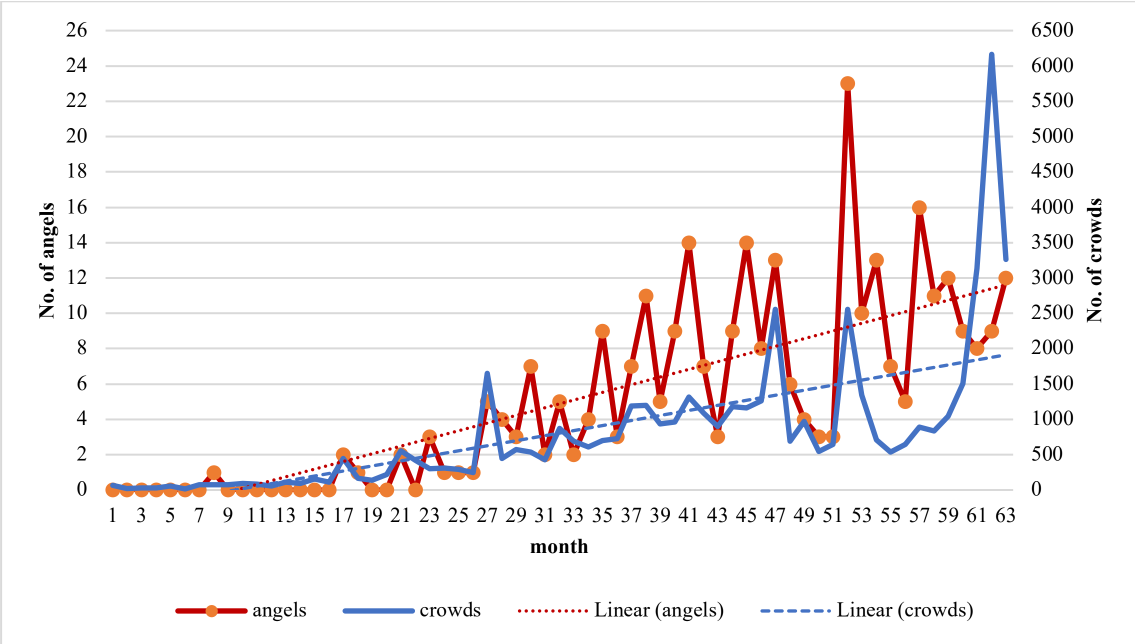
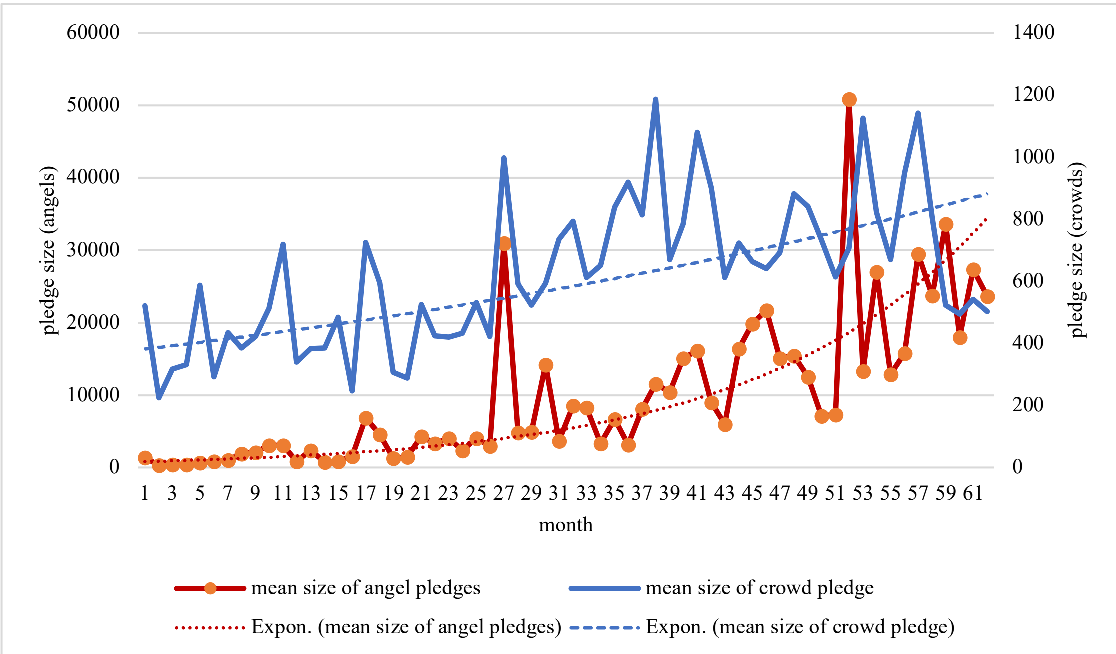


Figure 4.6 Average Size of Pledges by Investor Type and Month with Fitted Trends



4.3.4 Campaign dynamics

The temporal funding dynamics suggest significant differences between successful and unsuccessful campaigns. As an example, we plot the progression curves (i.e., the cumulative percentage of funding goal fulfilled) for a successful and an unsuccessful campaign with the same funding goal (£100,000) and a comparable number of pledges (Figures 4.7 and 4.8). Dots represent the percentage contribution per pledge considering the campaign goal, and the shaded area shows the cumulative percentage raised. The progression curve for the successful campaign shows several moments at which the curve rises sharply. These "jumps" correspond to high-contribution pledges. For simplicity, we will regard pledges accounting for more than 10% of the funding goal for a campaign as ***jumps*** (these pledges also correspond to the top 1% pledges in terms of percentage contribution)**.** The successful campaign received three jump pledges contributing 35%, 10%, and 20% of the goal. The progression curve for the unsuccessful campaign shows no jump pledges.

We observe a similar pattern for most successful and unsuccessful campaigns, suggesting jumps play a pivotal role in the success of campaigns. In general, successful campaigns had eight times more jump pledges compared to unsuccessful campaigns (3.54 vs. 0.46). However, these high-contribution pledges do not fulfil the entire funding needs for a successful campaign. On average, jumps account for about 54.16% of a campaign's goal (median of 11.11%). Hence, campaign success depends on pledges from more investors than only those associated with the high-contribution pledges.

We also observe that both the crowd and angel investors make jumps, but there is a concentration of angel jumps in larger campaigns. As a result, angels contribute more to the funding goal of large campaigns, but the crowd also seems to be playing a fundamental role (see Table 4.4).

Table 4.4 Summary Statistics on Jump Pledges

	Successful Campaigns (*N*=456)	**Failed Campaigns** (*N*=695)
Number of Jump Pledges per Campaign	3.54	0.46
Total Contribution of Jump Pledges per Campaign	0.72	0.08
	Angel Jumps (*N*=823)	**Crowd Jumps** (*N*=1,111)
Share of Jumps Associated with Large Campaigns	0.74	0.41
Average Size of Jumps*	0.47	0.21
Average Size of Jumps in Large Campaigns*	0.33	0.15

*Measured as the share of contribution to the campaign funding goal.

Figure 4.7 Campaign Progression for a Successful Campaign

(the campaign reached 129% of the £100,000 goal with three pledges contributing ≥ 10%)

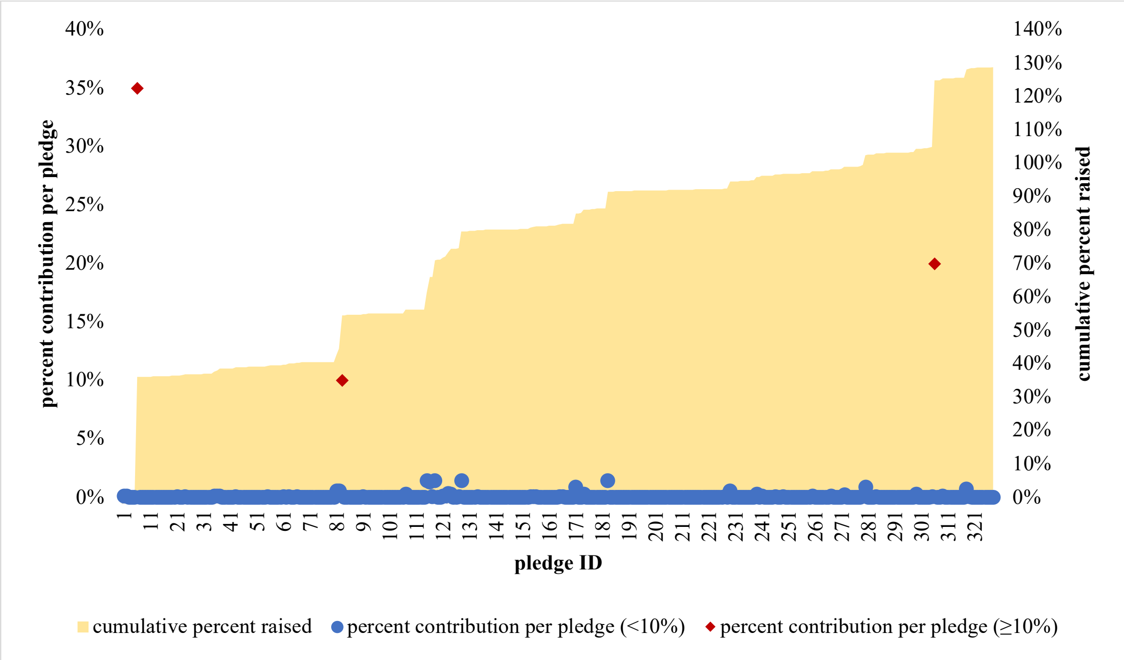
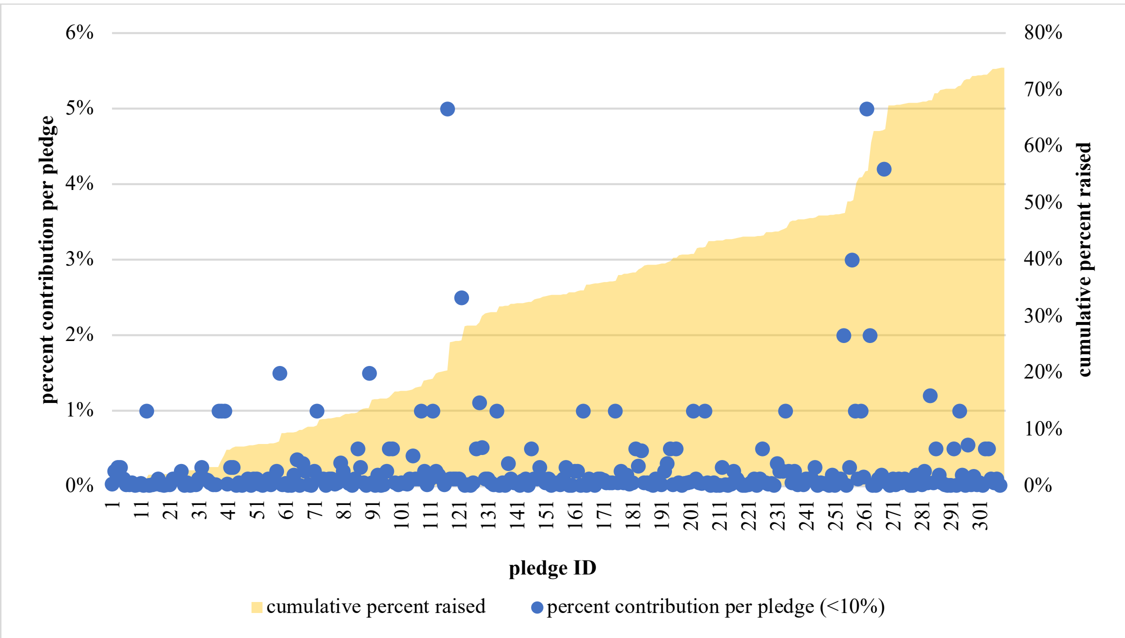


Figure 4.8 Campaign Progression for an Unsuccessful Campaign

(the campaign reached 74% of the £100,000 goal without any single pledge contributing ≥ 10%)



Finally, a higher percentage of angel jumps in successful campaigns (vs. unsuccessful campaigns) took place during the public launch period (64% vs. 46%), suggesting the importance of jump observability. However, the dynamics of inter-investor information flow are still unclear because we do not know when and how angel jumps influence a campaign's success. Understanding these dynamics will allow us to determine whether angels dominate the platform, reducing the influence of crowd investors, or whether the co-existence of angels and crowd investors provides significant benefits for investors and entrepreneurs.

4.4. Empirical Analysis

To study whether and how jumps, especially jump pledges by angels, influence the behaviour of investors on this platform, we adopt a fixed-effects lognormal model of pledge value:

$$Log\ (Pledge\ Value_{ijt}) = \beta Jump\ Metrics_{jt} + \gamma Campaign\ Dynamics_{jt} + \delta Investor\ Dynmaics_{it} + \theta Campaign\ Attributes_{j} + \mu_i + v_t + \epsilon_{ijt} \quad (4.1)$$

The dependent variable $Pledge\ Value_{ijt}$ denotes the amount pledged by investor i in campaign j at investment occasion t, and *Jump Metrics* represents a vector of our independent variables. *Campaign Dynamics*, *Investor Dynamics*, and *Campaign Attributes* are vectors of control variables that reflect campaign- and investor-specific, time-variant, and time-invariant features (we will specify below). The vectors of parameters β, γ, δ, and θ correspond to model coefficients, μ_i captures investor-level fixed effects, v_t includes yearly and day-of-week dummies, and ϵ_{ijt} represents independently and identically distributed normal error terms.

We created two independent variables: *Jump Occurred* and *Angel Jump*. *Jump Occurred* is an indicator variable equal to one once a campaign has received the first jump pledge, and zero any time before that, allowing us to test if a high-contribution pledge serves as a signal of campaign quality and whether it impacts subsequent investor behaviour (H1). *Angel Jump* is an indicator variable equal to one if the most recent jump to a campaign is made by an angel with a visible profile, and zero otherwise, allowing us to test the impact of an angel-generated signal (H2). The value of *Angel Jump* is updated only when a new jump occurs.

We also included several control variables in our model. Because investors are likely to perceive jumps accounting for 90% versus 20% of a campaign goal differently, we included *Jump Size* as a control. This variable measures the percentage contribution to the funding goal of the most recent jump made to the campaign (it updates when a new jump occurs). Because the effect of a signal is likely to diminish over time (Estrin and Khavul, 2016), we included *Jump Recency* as an additional control that corresponds to the number of days passed since the most recent jump.

We also included linear and squared terms of *Cumulative Percent Raised* for each campaign to control for the (possibly non-linear) effect of a campaign's fundraising progress and investor herd behaviour. Previous research has shown herd behaviour can occur when campaigns are close to reaching their funding goal (Agrawal et al., 2014). Considering that investors monitor the campaign's progression and accumulate knowledge (Hu and Gorbatai, 2015), follow-up investments in the same campaign are likely to differ from initial investments. Therefore, we included *Investor Campaign Experience* as an additional control that records the number of times an investor has previously invested in the campaign. To account for angels' sectoral experience and habitual investment behaviour (Maula et al., 2005), we included *Investor Sectoral Experience* dummy (taking the value one if the investor has previously invested in campaigns of the same sector, and zero otherwise).

We also accounted for observed heterogeneity across investors by including control variables such as *Investor Cumulative Amount Pledged* (calculated across all campaigns) and *Days Since Investor's Last Pledge* (to account for investor-specific recency effects). We also controlled for the impact of entrepreneur- and campaign-related factors such as the percentage of equity offered to investors (*Campaign Equity Offered)*, the effect of time pressure (*Days Until Campaign Expiration)*, and the interaction between entrepreneurs and investors during the private launch period (*Private Launch Pledge)*. Further, to control for competitive effects across campaigns, we included *Daily Number of Active Campaigns,* which counts the number of active campaigns on the same day of the pledge. Finally, year-specific dummy variables and day-specific dummy variables were included to control for yearly trends and day-specific factors, respectively.

4.5. Results and Discussion

4.5.1 Results summary

Table 4.5 (Models 1 through 6) and Table 4.6 (Models 7 through 10) present the main results. We report the results of the model with *Jump Occurred* (*JO*) as the independent variable using the entire sample to test *H1* (Model 1) and a full model with *Angel Jump* (*AJ*) to test *H2* (Model 2). We also estimate models for angels and crowd investors separately using standardized variables to test *H3* (Models 3 and 4). Finally, to test *H4a* and *H4b,* we repeat the analysis with standardized variables but split the sample by campaign size (Models 5 and 6). We further report the four sub-models for angels and crowd investors in large and small campaigns (see Models 7 through 10).

Consistent with *H1*, we find that a jump pledge positively affects the amount invested by subsequent investors (Model 1: β_{JO} = 0.127, *p-value*<0.001). The increase is significant as investors pledge 13.5% (0.135 = $e^{0.127} - 1$) more in a campaign in which previously a jump pledge had occurred, compared to when no previous jump pledge was present. When the jump pledge in a campaign is from an angel investor, we observe an additional positive impact, even after controlling for the jump. If the jump pledge is from an angel investor subsequent pledges increase by an extra 6.0%, supporting *H2* (Model 2: β_{AJ} = 0.058, *p-value*<0.001). We also note that the signaling effect of jumps decays over time as we find a negative effect of *Jump Recency* (Model 2: β_{JR} = -0.003, *p-value*<0.001). We find that an angel jump increases the amount per pledge by 7.0% for angels and 5.5% for the crowd. To explore differences in behaviour between angels and crowd investors, we conducted a split-sample analysis by investor type using standardized variables. We find that *Angel Jump* has a greater positive impact on angels compared to crowd investors (Model 3: β_{AJ} = 0.015, *p-value* = 0.079; versus Model 4: β_{AJ} = 0.012, *p-value*<0.001) supporting *H3* and suggesting angels react more positively to signals sent by their peers than by crowd investors.

Using standardized variables, split-sample analysis by campaign size shows that the positive effect of *Angel Jump* is significant in large campaigns (Model 5: β_{AJ} = 0.009, *p*-value<0.001) but insignificant in small campaigns (Model 6: β_{AJ} = 0.003, *p-value* = 0.460). This supports the argument that investors perceive angel jumps as costly signals only in large campaigns, hence, influencing subsequent pledges. In contrast, angel jumps in small campaigns do not change subsequent pledge behaviour, suggesting that lower-valued jumps are not costly to replicate and hence not perceived as effective signals of campaign quality. These results support the signal costliness hypotheses (*H4a* and *H4b*). Consistent with the results from the analysis based on the entire sample, in Models 5 and 6, our results suggest that the effect size of *Angel Jump* is greater in large campaigns than in small campaigns for all types of investors. We find that a previous angel jump increases subsequent pledges by 14.1% and 12.6% in large and small campaigns, respectively. In addition, the differences in beta coefficients for the models of investor type by campaign size confirm that Angel Jump has a greater impact in large campaigns (for angels compare Models 7: β_{AJ} = 0.030, *p*-value<0.001 vs. Model 8: β_{AJ} = 0.027, *p*-value = 0.069; for the crowd compare Model 9: β_{AJ} = 0.009, *p*-value<0.001 vs. Model 10: β_{AJ} = -0.001, *p*-value = 0.843). Again, these results further support *H4a* and *H4b.*

Table 4.5 Model Results

	Model 1 Pooled	Model 2 Pooled	Model 3 Angel	Model 4 Crowd	Model 5 Large Campaign	Model 6 Small Campaign
Angel Jump		0.058***	0.015*	0.012***	0.009***	0.003
		(0.008)	(0.009)	(0.002)	(0.002)	(0.004)
Jump Occurred	0.127***	0.111***	0.111***	0.020***	0.015***	0.045***
	(0.009)	(0.009)	(0.011)	(0.002)	(0.003)	(0.004)
Jump Size	-0.004	-0.004	-0.008	-0.001	-0.004	-0.002
	(0.004)	(0.004)	(0.008)	(0.002)	(0.006)	(0.002)
Jump Recency	-0.003***	-0.003***	-0.066***	-0.018***	-0.020***	-0.013***
	(0.0002)	(0.0002)	(0.010)	(0.002)	(0.002)	(0.004)
Cumulative Percent Raised	-0.013***	-0.015***	-0.132***	-0.003	0.024**	-0.004
	(0.005)	(0.005)	(0.021)	(0.004)	(0.009)	(0.008)
Squared Cumulative Percent Raised	0.0002	0.0002*	0.109***	-0.002	-0.311***	0.001
	(0.0001)	(0.0001)	(0.020)	(0.004)	(0.054)	(0.007)
Days Until Campaign Expiration	0.039***	0.039***	0.043***	0.031***	0.036***	0.021***
	(0.003)	(0.003)	(0.014)	(0.003)	(0.003)	(0.005)
Campaign Equity Offered	-0.003	-0.006	0.041***	-0.006***	-0.025***	0.024***
	(0.006)	(0.006)	(0.011)	(0.002)	(0.003)	(0.004)
Private Launch Pledge	0.122***	0.116***	0.003	0.028***	0.035***	-0.015***
	(0.013)	(0.013)	(0.013)	(0.003)	(0.004)	(0.006)
Daily Number of Active Campaigns	-0.001*	-0.001*	0.020	-0.007***	-0.007**	-0.018***
	(0.0007)	(0.0007)	(0.012)	(0.003)	(0.003)	(0.005)
Days since Investor's Last Pledge	0.046***	0.045***	0.058***	0.043***	0.048***	0.028***
	(0.002)	(0.002)	(0.011)	(0.002)	(0.002)	(0.004)
Investor Cumulative Amount Pledged	-0.061***	-0.061***	-0.019	-0.133***	-0.126***	-0.085***
	(0.002)	(0.002)	(0.016)	(0.003)	(0.004)	(0.007)
Investor Campaign Experience	0.243***	0.242***	0.060***	0.059***	0.059***	0.027***
	(0.008)	(0.008)	(0.007)	(0.002)	(0.003)	(0.004)
Investor Sectoral Experience	0.030***	0.030***	0.025**	0.012***	0.016***	-0.006
	(0.005)	(0.005)	(0.010)	(0.002)	(0.003)	(0.004)
Observations	144,890	144,890	8,492	136,398	112,394	32,496
BIC	339,913.900	339,850.500	17,857.510	132,671.000	121,996.300	23,372.360

*Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1. All models include an intercept. Model 3 through 6 estimated using standardized variables; we report beta coefficients. Standard errors in parentheses.*

Table 4.6 Results by Investor Type and Campaign Size

	Model 7 Angel Large Campaign	Model 8 Angel Small Campaign	Model 9 Crowd Large Campaign	Model 10 Crowd Small Campaign
Angel Jump	0.030***	0.027*	0.009***	-0.001
	(0.011)	(0.015)	(0.002)	(0.005)
Jump Occurred	0.454***	0.074***	0.005*	0.041***
	(0.031)	(0.014)	(0.003)	(0.004)
Jump Size	-0.021	-0.006	-0.003	-0.001
	(0.030)	(0.007)	(0.006)	(0.002)
Jump Recency	-0.043***	-0.040***	-0.016***	-0.010**
	(0.014)	(0.015)	(0.002)	(0.004)
Cumulative Percent Raised	-0.226***	-0.001	0.051***	-0.003
	(0.053)	(0.028)	(0.009)	(0.009)
Squared Cumulative Percent Raised	0.744**	0.004	-0.417***	0.00008
	(0.354)	(0.025)	(0.053)	(0.007)
Days Until Campaign Expiration	0.051***	0.050***	0.037***	0.018***
	(0.018)	(0.017)	(0.003)	(0.005)
Campaign Equity Offered	-0.006	0.056***	-0.026***	0.020***
	(0.014)	(0.015)	(0.003)	(0.004)
Private Launch Pledge	-0.007	-0.019	0.038***	-0.013**
	(0.016)	(0.018)	(0.004)	(0.006)
Daily Number of Active Campaigns	0.024	0.006	-0.010***	-0.021***
	(0.016)	(0.017)	(0.003)	(0.005)
Days since Investor's Last Pledge	0.052***	0.055***	0.048***	0.027***
	(0.014)	(0.017)	(0.002)	(0.004)
Investor Cumulative Amount Pledged	0.005	-0.050	-0.135***	-0.090***
	(0.019)	(0.031)	(0.004)	(0.007)
Investor Campaign Experience	0.082***	0.011	0.056***	0.034***
	(0.010)	(0.009)	(0.003)	(0.004)
Investor Sectoral Experience	0.036***	-0.001	0.015***	-0.007*
	(0.013)	(0.013)	(0.003)	(0.004)
Observations	5,859	2,633	106,535	29,863
BIC	12,773.250	4,133.809	102,732.500	18,010.440

*Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1. All models include an intercept and are estimated using standardized variables; we report beta coefficients. Standard errors in parentheses*

4.5.2 Additional analyses and robustness checks

Alternative identification approach for angel investors

We identified angels based on the total amount invested on the platform, an approach that could potentially leave out angels not particularly active or who have joined the platform in a later period of the sample. For example, an inactive angel or an angel who joined the platform towards the end of the sample period might make a single large pledge but might not meet the top 1% total investment threshold. To account for such instances, we tested our hypotheses using alternative identification approaches (see Appendix B, Table B1). We identified the top 1% of investors considering three alternatives: (1) the value of the largest pledge, (2) the average value pledged per campaign, and (3) the average value per pledge. The alternative specifications classify 510, 509, and 510 investors as angels, respectively, with an overlap with the original classification of 67%, 70%, and 78%. Further, to ensure that we accurately capture offline angels, we also classified as angels those investors who have made at least one jump and one pledge in the private launch period. This resulted in 726 investors and a 54% overlap with our original approach. We find that under all four alternative classification approaches, *Angel Jump* has a positive and significant impact on subsequent pledges (see Models 11 to 14, Table B1 in Appendix B). Hence, the impact of angel jumps is robust to the criteria used for angel identification.

Alternative jump definition

As an additional robustness check, we tested our hypotheses using an alternative jump definition that relies on absolute monetary value. In this scenario, we classify pledges greater than £20,000.50 (i.e., top 1% in terms of value per pledge) as jumps. Results with this alternative specification are again consistent with the main model results (see Table B2 in Appendix B).

Follow-up investments

Signal effectiveness could also depend on initial versus follow-up investments. We study follow-up investments using two approaches: firstly, we look at follow-up investments by an investor within the same campaign and, secondly, we evaluate differences in investments in ventures seeking initial versus higher rounds of financing. Although we controlled for follow-up investments in Models 1 through 10 (see Tables 4.5 and 4.6) using the *Investor Campaign Experience* variable, here we provide an additional analysis using models estimated separately for different sample splits: initial investments versus follow-up investments.

We observe that 9,008 investors have made follow-up investments to the same campaign. We find *Angel Jump* having a greater impact on initial investments (Model 18: $\beta_{AJ} = 0.065$, p-value<0.001,) compared with follow-up investments to the same campaign (Model 19: $\beta_{AJ} = 0.052$, p-value<0.001). As for ventures running multiple rounds of fundraising campaigns,[20] we

[20] We also controlled for the impact of follow-up investments across multiple rounds of the same venture by including a dummy variable (*Investor Previous Round Experience*) indicating whether an investor had already invested in a previous round. We find that the impact of angel jumps on investment behaviour is robust to the

observe that 103 ventures have successfully raised funds from 223 campaigns.[21] We distinguished investments in initial and higher (≥ 2) rounds and repeated our analysis. We find a stronger effect of *Angel Jump* on investments made to initial rounds (Model 20: $\beta_{AJ} = 0.083$, *p*-value<0.001) compared to investments made to campaigns seeking additional rounds of financing (Model 21: $\beta_{AJ} = 0.046$, *p*-value<0.001).

Consistent with arguments that signals are more effective when information asymmetries are more severe (e.g., Chen et al., 2012), our results show that angel jumps have a stronger positive impact on investors pledging in initial versus follow-up investments.

Investor syndicating behaviour

Angels typically engage in co-investing and syndicating behaviour (Mason et al., 2016). In our platform, angels who co-invest in the campaign's private launch period are more likely to build informal offline connections. These connections could provide an alternative explanation for the results we find and the role of ECF platforms in open and public information dissemination to be less important for the effects we find.

To test for these alternative explanations, we focus on 342 angels who pledged during the private launch and build a 342-by-342 adjacency matrix of whether two angels have co-existed in any campaign's private launch period or not. The density of this proxy network is very low (0.08), meaning that among the 58,311 (342*341/2) potential angel pairs, only 4,722 engaged in co-investment in private launch periods, and 77% of these pairs co-invested only once. Therefore, our results indicate very limited evidence of (informal) syndication or offline networking. Instead, the signaling effects occur due to the information flow between investors facilitated by the digital channel.

4.5.3 Discussion

The digitization of early-venture funding through ECF platforms provides the opportunity to close funding gaps by serving ventures that institutional investors are unwilling to consider. It facilitates the exchange between many common investors and entrepreneurs, overcoming the difficulties typically posed by offline channels, such as access to angels, physical distance, and the lack of social capital. In the past years, the venture diversity (in sector and scale), the upside potential of early-stage ventures, and the convenience offered by ECF platforms have attracted

inclusion of the additional investment round control ($\beta_{AJ} = 0.054$, *p-value*<0.001). Finally, models by investor type are also consistent with our overall results. Detailed results available from the authors upon request.

[21] We only focus on campaigns that were successful and reached their funding goal in more than one round.

sophisticated and professional investors such as business angels who now invest alongside small non-professional investors. The influx of large investors, although providing opportunities to entrepreneurs, could constitute a threat to the democratizing role of ECF platforms if large investors crowd out smaller and non-professional ones.

Our study sheds light on this issue and responds to a call for evidence-based research on the interaction between angels and the crowd (Hellmann and Thiele, 2015; Hornuf and Schwienbacher, 2016). To the best of our knowledge, ours is the first study to rely on investors' pledging decisions to empirically identify and categorize ECF investors, adding to the insights obtained through previous surveys and interviews (e.g., BBB and UKBAA, 2017).

Our results show that the growth of large campaigns and the presence of angel investors on the ECF platform go hand-in-hand. Angels invest in large campaigns and are essential to their success on the platform. Despite the growth in angel investors, we find crowd investors still play an important role in bridging funding gaps in large campaigns. For small campaigns that do not attract angel investments, crowd investors are instead the fundamental source of funding. This angel-crowd complementarity suggests that ECF has maintained its democratic credentials.

In addition, the presence of angels and the visibility of their funding behaviour via digital ECF platforms help reduce information asymmetry in early-stage financing. Such asymmetries typically generate market frictions and inefficiencies. Angel's investment decisions, and specifically their high-contribution pledges, act as informative signals of venture quality. Hence, crowdfunding platforms facilitate information flow from more experienced and possibly better-informed investors to the crowd. In a context where regulators fear for the financial health of small non-professional investors, our results suggest that the digital environment of ECF platforms with real-time and fast-paced flows of information benefit novice investors as they can easily observe the investment behaviour of angels.

Although a large body of ECF literature has explored the effects of entrepreneur-generated signals on investor behaviour (e.g., Ahlers et al., 2015), how investors interact and how information flows among investors is seldom studied. We provide an important contribution in this regard. We find that the digitization of venture financing has not only allowed entrepreneurs to communicate easily to a larger and more diverse group of investors, it has also allowed investors to observe the decisions of other investors, facilitating inter-investor information flow. Hence, the digitization of early-stage finance has been able to reduce the limits imposed by the need for physical and social proximity.

Our work also addresses the call for multidisciplinary crowdfunding research (McKenny et al., 2017). We combine insights from information economics, sociology, and entrepreneurship to shed light on the impact of investor-generated signals on ECF platforms. Although our results are novel and contribute to signaling research in crowdfunding literature, they are also consistent with more general signaling theories of *social proximity* (e.g., Cowgill et al., 2009) and *signal costliness* (e.g., Connelly et al., 2011). For example, we demonstrate that information flow between investors depends on the identity of the signal sender, signal recipient, and context.

4.6 Policy Implications

The regulator's support and sympathetic approach towards digital ECF (globally and especially in the UK) has increased the flow of capital to early-stage ventures and facilitated innovation. As ECF platforms evolve and mature, concerns arise regarding the protection of the interests of small investors. While some contend that the U.S. regulatory framework for ECF provides little protection to small investors (Shiller, 2015), others suggest that the UK regulators are too "fintech friendly" and compromise stringency in assessing investor qualification (Zhang et al., 2015).

For example, in the UK, the current regulatory framework requires investor self-certification as high-net-worth, sophisticated, or everyday (crowd) investors. In the ECF platform, we study, we find that a quarter of investors self-certified as high-net-worth individuals invested less than £500 over the entire period, whereas 2% of those self-certified as "everyday investors" invested more than £66,000 (our threshold for angel identification). These results raise concerns regarding the accuracy of the current investor self-assessment procedure of ECF platforms. It is necessary for regulators to ensure standardized information collection across platforms via in-depth questionnaires on investors' financial acumen, investment experience, qualifications, and wealth. More importantly, using the behaviour-based investor categorization that we employ in the current study, platforms could better segment investors and facilitate information flow by making these categories visible to platform members. Further, there is a need to educate inexperienced investors regarding the risks of investing in early-stage ventures. Currently, ECF platforms inform investors via "risk warning" pages, blogs, and forums. There is a need to explain various types of risks better and make risk warnings more visible on ECF platforms.

In addition, there is evidence that some entrepreneurs send false signals to the market by making a large anonymous investment in their own ventures (Burtch et al., 2013). Not surprisingly, the FCA has recently raised concerns regarding insufficient information transparency on digital funding platforms and has proposed to refine its current regulations on the crowdfunding sector (FCA, 2018). Indeed, signaling across investors plays a significant role in ECF platforms, and anonymous high-contribution pledges could pose a risk to investors less able to verify investors' credentials. In light of these concerns, to protect investors in general and crowd investors in particular, we urge regulators to consider greater transparency and information disclosure on ECF platforms for large pledges above a certain threshold. Platforms could require investors pledging more than 10% of a campaign's funding goal to disclose their real identities (instead of usernames), professional social network information (e.g., LinkedIn or Crunchbase pages), or authenticated personal webpages. However, it should be also noted that enforcing identity disclosure may discourage large investors that are very conscious over privacy concerns. Regulators may need to strike a healthy balance between protecting small investors' benefits (through identity disclosure) and keeping these platforms appealing to large investors who are privacy-sensitive.

Finally, considering that many successfully funded ventures on ECF platforms eventually fail (Signori and Vismara, 2016), there is a greater need for regulators to impose standardized due diligence procedures for platforms to protect all investors. Many ECF investors, including angels, rely on platforms to screen ventures. Although the FCA requires platforms to conduct due diligence, in practice, the background checks are not standardized across platforms. With the growth in funding volume raised by ECF platforms, such a lack of clarity is no longer desirable. Regulators ought to impose more rigorous and standardized risk assessment of ventures featured by ECF platforms. Our findings support FCA's recent focus on tightening the regulatory framework for platforms and the demand side (i.e., ventures) of the crowdfunding sector (FCA, 2018).

4.7 Conclusion

Our analysis of one of the UK's leading ECF platforms provides an optimistic outlook for the future of digital crowdfunding. With greater transparency and standardized regulation, we believe that digital crowdfunding platforms can continue to support the complementary co-existence of angels and the crowd, greatly facilitating early-stage finance.

Our study is not devoid of limitations. Even though the ECF platform we study is representative of other leading platforms, and we proposed a robust angel identification strategy based on pledging behaviour, future research could study the generalizability of our findings across platforms and alternative identification strategies. In addition, future research could explore in more detail the type of angels attracted by ECF platforms and whether angels treat ECF as a different asset class. As ECF grows, we expect to see greater involvement of angels, providing more opportunities to study their behaviour.

Additionally, there exists endogeneity concerns over the impact of campaign underlying quality on investor decisions. Our empirical models explicitly include a rich set of campaign-level attributes as proxies of unobservable quality of campaigns. Future research may consider incorporating campaign-level fixed effects to address such endogeneity concern.

Further, we discussed several ways to identify angel investors out from the crowd in main analyses and robustness check sections. However, future research can examine more alternative operationalization of jump pledges and uncover more effective investor-generated investment signals.

Finally, prior research has found that ventures with angel investments have higher survival and growth rates (Kerr et al., 2011). Thus, from a practical and policy perspective, it is important to study whether the long-term performance of ventures funded by angels on ECF platforms mirrors that of ventures that obtain funding via conventional means of finance. Although we find no evidence of syndication, investors (particularly angels) may accumulate social capital through co-investments and form syndicates as the ECF market matures. Hence, future research could explore whether syndicates emerge on digital platforms.

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Appendix A

Chapter 3 Study 3—Summary of Moderated Mediation Results

Figure A1 Moderation effect of service category: Willingness to Click

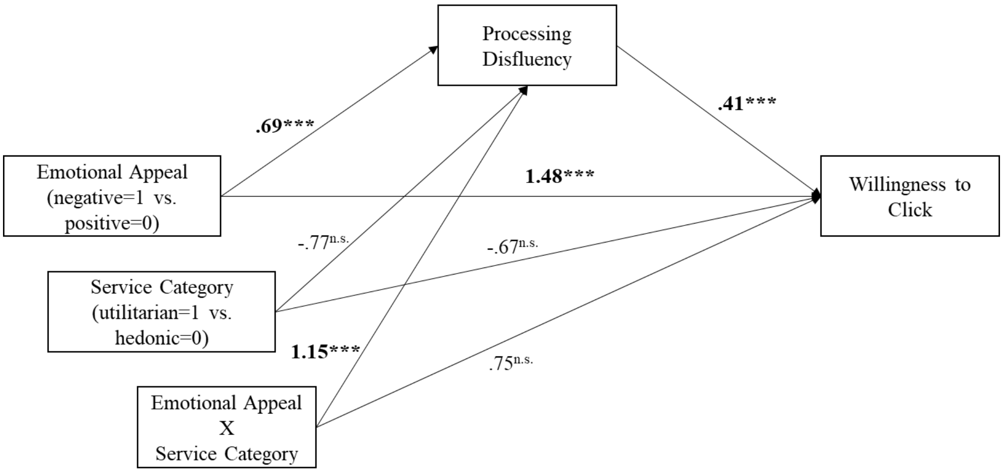


Figure A2 Moderation effect of service category: Willingness to Purchase

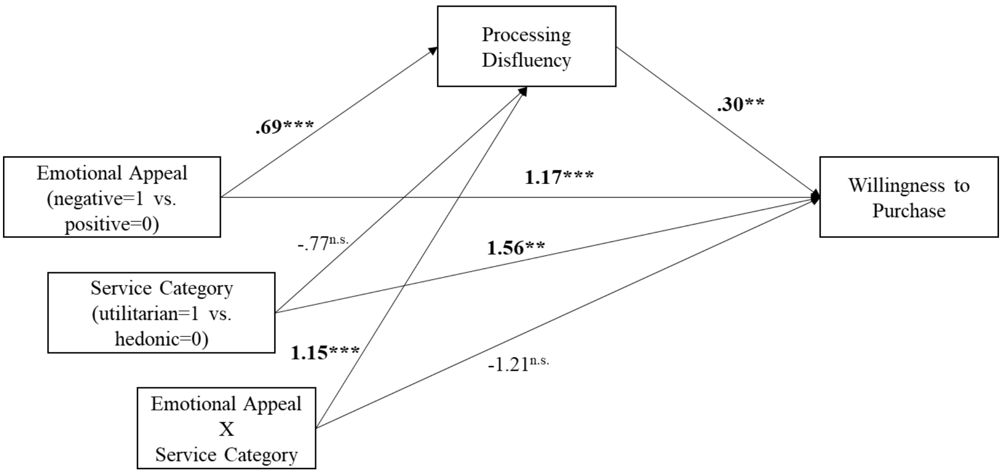


Figure A3 Moderation effect of service category: Ad Attitude

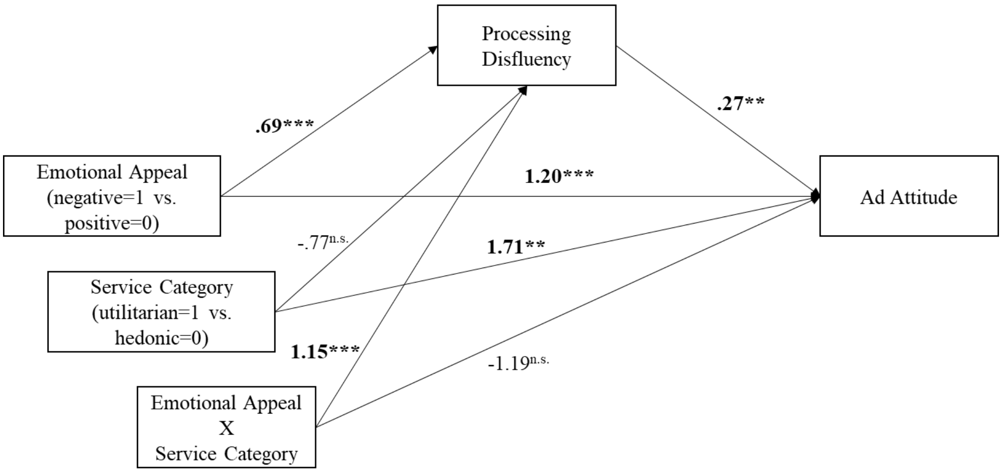
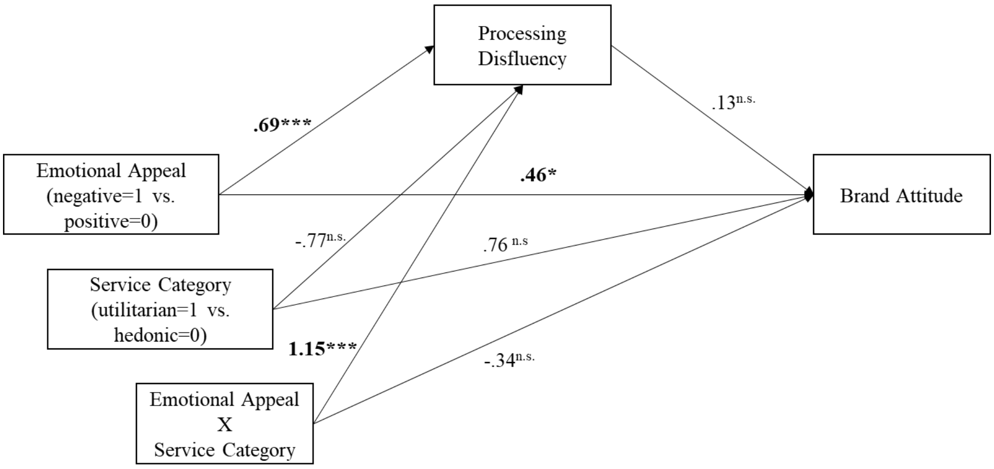


Figure A4 Moderation effect of service category: Brand Attitude



Appendix B

Chapter 4 Robustness Checks

Table B1 Alternative Angel and Jump Identification

	Model 11 Alternative Angel 1	Model 12 Alternative Angel 2	Model 13 Alternative Angel 3	Model 14 Alternative Angel 4	Model 15 Alternative Jump
Angel Jump	0.146***	0.171***	0.141***	0.027***	0.104***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Jump Occurred	0.023**	0.044***	0.057***	0.111***	1.443***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.054)
Control Variables Included	YES	YES	YES	YES	YES
Observations	144,890	144,890	144,890	144,890	144,890
BIC	399,915.500	399,714.200	399,993.000	339,908.800	398,057.900

*Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors in parentheses.*

Table B2 Follow-up Investments

	Model 18 Initial	Model 19 Follow-up	Model 20 Initial	Model 21 Follow-up
Angel Jump	0.065**	0.052**	0.083***	0.046***
	(0.030)	(0.023)	(0.008)	(0.011)
Jump Occurred	0.104***	0.078***	0.041***	0.176***
	(0.015)	(0.013)	(0.013)	(0.014)
Control Variables Included	YES	YES	YES	YES
Observations	20,431	32,507	22,131	17,411
BIC	36,432.290	77,245.790	40,393.640	39,869.220

*Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1. All models estimated using standardized variables; we report beta coefficients. Standard errors in parentheses.*