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Channel Usage, Product Attributes, and Return Behavior: An Empirical Analysis

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Abstract:

Adding a new channel or service generally increases overall sales revenue and lowers returns in omnichannel setups. Access to multiple channels reduces consumer search and transaction costs and information asymmetry regarding product fit. However, no research has examined how customers' channel usage influences their preference for product types and how that affects return rates. Using transaction data from a European furniture retailer that operates physical showroom stores, an online channel, and a catalog channel, we conduct fixed-effect regressions and a parallel mediation analysis to examine the purchasing and return behaviors of consumers who use multiple channels (multichannel consumers) and those who use a single channel (single-channel consumers). Our analysis indicates that the differences in return likelihood become less significant when specific product attributes are controlled for. Furthermore, we find that multichannel consumers are drawn to niche and experience products. Through an online experiment, we show that having access to multiple channels increases consumers' confidence about their perceived ability to make right product selections. This also increases their willingness to try new products, and purchase products that are more niche and experiential. However, these products often come with a higher degree of product uncertainty due to their specialized nature or need for physical interaction to fully assess the product, leading to a higher propensity for returns. Consequently, we find that the differential return likelihoods between multichannel and single-channel consumers can be attributed to product characteristics. The inclination of multichannel consumers to purchase niche and experience products, which inherently have higher return likelihoods, contradicts the common belief that multichannel consumers are less likely to return products because they have better information about product fit. Our study presents a new mechanism that clarifies the nuanced interplay between product attributes and consumers' multichannel usage and return behaviors. We discuss implications for product assortment, customer targeting, and channel distribution management.

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(Authors' names blinded for peer review)

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1. Introduction

The widespread growth of omnichannel retailing has redefined the way consumers interact with products and brands, merging the boundaries between online and offline channels (Bell et al. 2018). Among the many services such as ship-to-store (Akturk and Ketzenberg 2022) and buy-online-pick-up-in-store (Gao and Su 2017), Warby Parker and other similar retailers have incorporated showroom stores into their business model. These stores serve as a physical space where customers can personally interact with the products, experience their texture, and seek advice from knowledgeable store associates regarding the fitting of the products. Accordingly, studies have shown that showrooms are effective in increasing sales revenue, drawing in new customers, and reducing the number of product returns (Bell et al. 2020). These showrooms, also known as stores with zero inventory, are distinct from traditional brick-and-mortar stores because they do not stock any products. Consumers who visit these showrooms typically make their purchases in-store and then await the delivery of their orders.

Despite existing research documenting reductions in consumer search costs and informational asymmetries about product fit provided by multiple channels (Dzyabura and Jagabathula 2018, Gao and Su 2017, Petersen and Kumar 2009), the empirical understanding of multichannel consumer purchasing and return behaviors remains limited. With improved information regarding product fit, which decreases product uncertainty, omnichannel services tend to increase sales and decrease return rates. In addition, omnichannel research typically assumes that differences in the types of product purchased by consumers are mainly driven by channel-specific characteristics. For example, physical stores may be more effective in conveying tactile information about products with high levels of touch and feel relative to nondigital channels (Bell et al. 2018). Moreover, products with different levels of uncertainty vary in their likelihood of being returned (Hong and Pavlou 2014). However, no previous research has explored how customers' choice of channels (multichannel vs. single-channel) influences their preference for different product types and the subsequent impact on return rates.

Multichannel consumers use different channel options provided by retailers when they make purchases. On the other hand, single-channel customers consistently stick to a single channel, either online or offline, for their shopping, regardless of a retailer's channel strategy (Timoumi et al. 2022). The implications for retail operations are significant, with return rates in the United States averaging 17% (or $760 billion) of total U.S. retail sales (NRF and Appriss Retail 2021). Understanding these trends is crucial for retailers because returns represent a significant cost and operational challenge within the omnichannel ecosystem.

In this paper, through empirical analysis of 294,348 transactions data from an omnichannel furniture retailer in a European country, we explore a new mechanism: the nuanced interplay between product attributes and multichannel shopping behaviors. We conduct a series of fixed-effect regressions to compare the purchasing and return behaviors of multichannel consumers versus single-channel consumers. We further conduct a parallel mediation analysis to clarify the mediating role of product attributes (niche and experience levels) in the relationship between multichannel usage and likelihood of return. Moreover, we employ Heckman selection method to address potential selection bias by consumers in their preferred channels, control function to ameliorate omitted variable bias, and risk-set matching to account for consumers' greater tendency to gravitate toward using multiple channels in their purchases due to a more intense consumption trajectory.

Although multichannel consumers benefit from a wealth of information, leading to more accurate purchase decisions and potentially lower return rates (Bell et al. 2018), our analysis suggest that differences in return behavior become less significant when controlling for individual product effects. Furthermore, we find that multichannel consumers are drawn to niche and experience products, which is consistent with the understanding that using multiple channels allows consumers to leverage the breadth of information available online to discover and evaluate less mainstream products. However, through an online experiment, we find direct evidence that having access to multiple channels also increases consumers' confidence about their perceived ability to make right product selections. In turn, this increases their willingness to try new products, as well as purchase products that are more niche and experiential. Because niche products often come with a higher degree of uncertainty due to their specialized nature, this leads to a higher propensity for returns. Similarly, experiential products, which require physical interaction to fully evaluate, carry a higher risk of returns due to the experiential gap that might exist between online information and actual product experience. Consequently, we find that the differential return behaviors between multichannel and single-channel customers can be attributed to consumers' self-evaluation of their confidence and the types of product they purchase, in addition to channel-specific drivers as documented in the literature. The propensity of multichannel consumers to buy niche and experiential products, which inherently have higher return rates, contrasts with the initial hypothesis that multichannel consumers are less likely to return products due to increased information availability. This finding contributes a new perspective to the existing literature on omnichannel retailing and consumer behavior, particularly in the context of furniture retail.

Based on the empirical insights, we develop a consumer choice model to predict the choice of channel used to purchase a product and the subsequent return rate. In practice, we can leverage the prediction model to inform the focal retailer on the choice of channel to distribute niche and experience products. Based on a cross-validation procedure, our model achieves an average of 93% accuracy and Area under the ROC Curve (AUC) score of 0.91 in predicting matches (i.e., the predicted channel by our choice model *matches* the observed channel in the holdout sample). Our analysis shows that the average return rates are consistently *lower* when the predicted channel matches the observed channel compared with cases when they do not match at the aggregate level and across both the single-channel and multichannel consumer sub-samples. We repeat the procedure and conduct two additional analyses to examine the consistency of the main results at the product type level, that is, niche versus popular products, and experience versus search product. Overall, we find that the average return rates are lower when the predicted channel from our choice model matches that of the observed channel across the three sample categories (overall, single-channel, and multichannel), between niche and popular products, and between experience and search products.

2. Literature Review

Our study contributes to three streams of literature on empirical omnichannel retail services, consumer returns, and multichannel customer management. The first research includes studies documenting the effects of adding a new physical channel such as showroom (Bell et al. 2018) or traditional brick-and-mortar (Kumar et al. 2019, Avery et al. 2012) stores by an online retailer, or an online channel by offline retailers (Geyskens et al. 2002). This research also examines the impact of introducing a new omnichannel service such as ship-to-store (Bell et al. 2020, Gallino et al. 2017, Akturk and Ketzenberg 2022) or buy-online-pick-up-in store (Gao and Su 2017) on a variety of performance metrics. While adding a new sales channel might compete with existing ones, overall sales revenue usually increase in omnichannel setups in the extant literature (see Timoumi et al. (2022) for a review). This is because the introduction of an additional channel or a new service tend to reduce search costs and product uncertainty (Hong and Pavlou 2014) and makes shopping more convenient for customers, which, in turn, also lowers product return rates. For example, in the context involving online retailers introducing an experience-centric offline store (or zero inventory store), Bell et al. (2020) show that after consumers experience the physical store, they spend more, shop at higher velocity, and are less likely to return products. Moreover, Bell et al. (2018) provide empirical evidence that an exclusively online seller can gain from incorporating showrooms, leading to a decrease in product returns, as customers have the opportunity to visit a physical location to interact with and assess a product before making a purchase. Yet, most studies focus on a set of homogeneous products that are rich in nondigital attributes (e.g., footwear, eyewear), or low-involvement, search goods (e.g., men's fashion apparel, home goods). Our research delves into a new context, considering furniture products with different levels of consumer-involvement and information uncertainty across channels (Ofek et al. 2011). We find that consumers using multiple channels may have higher return rates, as they tend to purchase products that are more niche and experiential, compared to single-channel shoppers. In doing so, we contribute a new mechanism (i.e., product attributes) explaining the differential return behaviors between multichannel and single-channel customers.

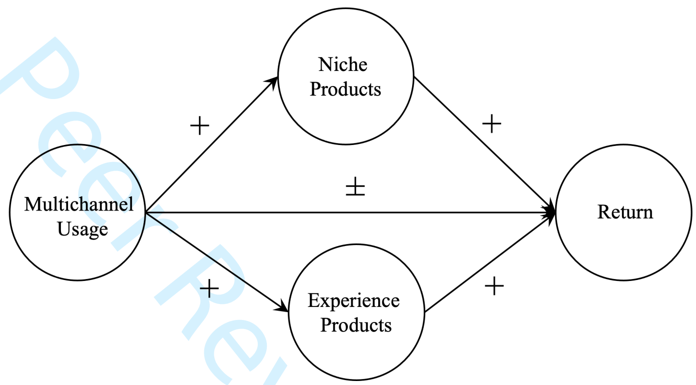
In the second research stream, the extant consumer returns literature focuses on return management (acquisition, processing, and disposition of returns) mainly from retailers' perspective, and identifying return policies such as restocking fee, money-back guarantee, return period, and channel restrictions influencing consumer returns (see Abdulla et al. (2019) for a comprehensive review). This stream of literature classifies customer heterogeneity *ex post* or *ex ante*. In the former, existing studies model heterogeneity by segmenting customers into low and high types based on *ex post* product fit probability (i.e., the probability of a consumer satisfying a purchase) (Fruchter and Gerstner 1999), product valuation (Su 2009, Hsiao and Chen 2014, Akçay et al. 2013), or return hassle costs (Fruchter and Gerstner 1999, Hsiao and Chen 2012). In the latter, consumers are *ex ante* heterogeneous in terms of the probability of product fit (Fruchter and Gerstner 1999), the individual consumer's taste parameter or the likelihood of consumers within a segment knowing their product valuation *ex ante* (Shulman et al. 2009), the fraction of genuine versus opportunistic consumers (Shang et al. 2017), or the fraction of consumers who have a higher likelihood of returning when observing others returning product versus those immune to this effect (Xu et al. 2018). None of this research considers consumer heterogeneity based on channel usage *ex ante* and consumers' return behavior *ex post*. We bridge this gap; in doing so, we provide additional understanding of the underlying relationship governing multichannel consumer purchasing behavior, characteristics of purchased product, and their return propensity.

The third stream of research on multichannel customer management indicates that customers using multiple sales channels tend to be more profitable than those who use a single channel (Ketzenberg et al. 2020), especially when retailers employ a well-crafted marketing campaign with the right message and incentives (Venkatesan et al. 2007, Thomas and Sullivan 2005, Montaguti et al. 2016). Consequently, Venkatesan et al. (2007) identify factors that drive consumers to adopt additional sales channels, while Jerath et al. (2015) develop a model to understand and predict customers' multichannel behavior in a customer support setting based on data from a health insurance firm. Ketzenberg et al. (2020) develop a predictive algorithm to detect potential return abusers in a multichannel context. Previous studies have used survey or transaction data from apparel (Venkatesan et al. 2007), department store (Ketzenberg et al. 2020), or book (Montaguti et al. 2016) retail. We expand the literature by conducting our study in a new setting that involves furniture products with different levels of nichness and experiential attributes. We show that in the furniture retailing context, even after considering the higher return rates of multichannel consumers compared to their single-channel counterparts, the former generates higher revenue.

3. Theory Development and Hypotheses

This section proceeds in four parts. First, we hypothesize the effect of controlling for product on multichannel and single-channel consumers' return likelihood (H1). Second, we provide propositions from search-cost and individual psychology theories, as well as empirical findings from the existing literature, to conjecture multichannel consumers' tendencies to purchase niche products (P1) and the effect that niche products have on return rates (P2). Third, using a similar approach to develop P1 and P2, we provide propositions to posit multichannel consumers' tendencies to purchase experience products (P3) and the effect that experience products have on return rates (P4). Finally, we hypothesize multichannel consumers' return behavior via a parallel-mediation mechanism that involves product attributes (i.e., niche and experience levels) compared to their single-channel counterparts (H2). Figure 1 shows the product-attributes mechanism process model.

Figure 1: Product-attributes Process Model and Empirical Directionalities



Notes. + denotes positive association. ± denotes either positive or negative association.

3.1. Consumer Return Behavior and Product Attributes

Consumers who use multiple sales channels in their purchasing benefit from richer information about products, thereby alleviating uncertainty about product fit and increasing the accuracy of their purchase decision (Kushwaha and Shankar 2013, Venkatesan et al. 2007). The ability to leverage multiple channels for information gathering, such as online reviews, detailed product descriptions, and in-store experiences, could lead to a better match between the consumers' expectations and features of the actual product, thus decreasing the likelihood of returning a product post-purchase (Bell et al. 2018).

However, we posit that when controlling for the same product, the difference in return behavior between multichannel and single-channel consumers may become negligible because product attributes such as popular versus niche, and search versus experience, are held constant. This uniformity in product attributes means that the additional product information that multichannel consumers normally gather from different channels might not significantly influence their decision to return a product. This can result in non-differential return behavior of multichannel consumers compared to single-channel consumers who have access to the same product information.

From a product popularity standpoint, popular products often come with a wealth of information from various sources and have been vetted by a large customer base (Gu et al. 2012). This makes the information asymmetry between multichannel and single-channel consumers less pronounced since even single-channel consumers are likely to have enough information to make an informed decision. On the other hand, niche products are less known and have fewer reviews, so multichannel consumers often have an advantage as they can glean information from various channels to reduce uncertainty. However, when both consumer groups purchase the same niche product, they are equally exposed to the limited available information. Although some residual differences may still exist, the variations in terms of the likelihood of returns are likely to become less pronounced.

The distinction between search and experience products further clarifies this phenomenon. Search products are those whose qualities can be determined before purchase, making them less likely to be returned as consumers can assess their fit beforehand (Hong and Pavlou 2014). Experience products, on the other hand, require physical interaction to evaluate, and are thus more prone to returns. Multichannel consumers typically benefit from the ability to assess experience products both online and offline. Yet, when the product type is controlled for, both multichannel and single-channel consumers have the same level of product experience, leading to similar levels of post-purchase satisfaction and, consequently, similar return rates. Therefore, we hypothesize that:

Hypothesis 1 (H1): Controlling for the same product, multichannel consumers exhibit no significant difference in their likelihood to return a product compared to single-channel consumers.

3.2. Consumer Purchasing Behavior and Niche Products

Products that are commonly sold, known as popular products, generally have less ambiguity regarding their quality and suitability compared to niche items that are sold less frequently. In a multichannel retail environment, consumers can leverage the breadth of information available online to discover and evaluate products that are not mainstream. The online channel, with its extensive reach and depth, allows consumers to access online word-of-mouth such as specialized forums and product reviews, which might not be as readily available in traditional retail settings (Gu et al. 2012). Moreover, recommendation systems commonly deployed in online channel further amplify this effect by guiding consumers toward niche products that align with their unique preferences and past shopping behaviors (Brynjolfsson et al. 2011). This accessibility diminishes the search costs, which are traditionally higher for niche products due to their limited presence and reviews in physical stores. However, compared to single-channel consumers, multichannel consumers may have different levels of self-affirmation that is driven by their channel usage.

Consumers who have access to multiple channels may develop a higher level of confidence in their decision-making abilities. This is because multichannel environments provide a more comprehensive and nuanced view of products, including user reviews, detailed product descriptions about digital and nondigital attributes, and comparative pricing across different platforms. Access to this extensive information empowers multichannel consumers to make well-informed decisions, boosting their confidence in selecting the right products (Bearden et al. 2001). Armed with insights from multiple channels, multichannel consumers feel more capable of evaluating the attributes and quality of less familiar products. The increased confidence leads these consumers to be more adventurous in their purchasing habits, venturing beyond popular items to explore the less popular ones (Balasubramanian et al. 2005). Consequently, we conjecture that:

Proposition 1 (**P1**): Multichannel consumers are more likely to purchase niche products than single-channel consumers.

Niche products are characterized by their specialized nature, catering to specific customer preferences or requirements. Because of their unique nature, these products often come with a higher level of uncertainty for consumers (Hong and Pavlou 2014). There is usually limited customer feedback and fewer reviews available, making it difficult to assess product quality and satisfaction before buying. With fewer consumer trials and less collective knowledge to rely on, purchasing niche products involves a higher perceived risk. Since these products have limited visibility in the market, consumers' post-purchase experiences may not always align with their expectations based on the limited information they had. This leads to a higher likelihood of returns (Shang et al. 2019). Moreover, niche products, due to their distinctive features, lack of standardization, or targeted appeal, often vary in quality and performance. This further increases the chance of consumer expectations not being met, consequently contributing to the uncertainty and higher rate of returns observed after the purchase. Mainstream products, on the other hand, benefit from abundant market signals and reviews, which help calibrate consumer expectations more effectively.

Proposition 2 (**P2**): Niche products are more likely to be returned post-purchase.

3.3. Consumer Purchasing Behavior and Experience Products

Product uncertainty is influenced by the popularity and nicheness of the product, as well as by the experiential level of the good. Experience goods are items that are difficult to evaluate in terms of their usefulness before they are purchased (Nelson 1970, Hong and Pavlou 2014). Similar to the self-affirmation and confidence arguments in P1, consumers who engage with multiple channels are more inclined to purchase experience products due to the perceived enhanced capacity to assimilate comprehensive product insights from various touchpoints, thus reducing the experiential uncertainty inherent in such product. Experience products, by definition, require personal interaction to fully evaluate their value and non-digital attributes, such as testing the firmness of a mattress or the comfort of a lounge chair (Weathers et al. 2007). Multichannel consumers can leverage tactile feedback from offline channels such as a showroom store and the extensive information available online to form a more complete and confident assessment of these products before purchasing (Ofek et al. 2011). This omnichannel approach allows for a deeper experiential preview, simulating the usage of the product to a greater extent than what a single channel can offer. The synergy between the physical examination of products in-store and the additional information and reviews available online culminates in a richer, more informed consumer experience, making the purchase of high experiential level products more likely. Therefore, we posit:

Proposition 3 (**P3**): Multichannel consumers who use multiple channels are more likely to purchase experience products than single-channel consumers.

Experience products are typified by qualities that consumers can only assess accurately through direct interaction, such as fit, taste, or performance, which cannot be fully appreciated through indirect product representations like images or descriptions. This experiential gap often leads to a disparity between consumer expectations and the actual product experience post-purchase, thereby increasing the likelihood of return. Such products inherently carry a higher purchasing risk, where the potential for emotional and product dissonance is more pronounced due to the subjective nature of the evaluation. The inability to bridge the gap between expectation and experience prior to purchase, despite the presence of online reviews and detailed product descriptions, accentuates the challenge consumers face in making definitive purchasing decisions for these products. Therefore, the increased probability of a mismatch in personal satisfaction levels with experience products directly contributes to a higher rate of return.

Proposition 4 (**P4**): Experience products are more likely to be returned post-purchase.

3.4. Multichannel vs. Single-Channel Return Behavior

Multichannel consumers, who utilize various channels such as online stores, catalogs, and brick-and-mortar locations to make their purchases, are more likely to return products (Ketzenberg et al. 2020). In our context, this is due to the type of products purchased by multichannel consumers. The previous propositions suggest that these consumers are drawn to niche and experiential products, which by their nature, have a higher propensity for returns. Niche products often come with a higher degree of uncertainty due to their specialized nature and lack of widespread reviews, leading to a mismatch between expectations and reality post-purchase. Similarly, experiential products require physical interaction to assess their value fully, and without the ability to engage with the product pre-purchase in all dimensions, consumers may find that their expectations are not met upon actual use, prompting a return. This predilection for products that demand a higher degree of personalization and experiential satisfaction naturally results in a greater propensity for returns among multichannel consumers, as the risks associated with these product categories are more pronounced and the opportunity for experiential discrepancy is greater. Moreover, having access to multiple channels may lead to consumers' overconfidence in their ability to make right product selections. This further accentuates the mismatch rates between consumer expectations and actual product performance, leading to higher return rates.

Conversely, the argument for multichannel consumers having less likelihood to return products hinges on the abundance of information available across different channels, which can diminish uncertainty and lead to more satisfactory purchasing decisions. By engaging with multiple channels, consumers can access detailed product descriptions, reviews, and comparisons, which help them to form a more accurate expectation of the product. Furthermore, the opportunity to interact with products in-store provides tangible experiences that can validate the information found online, reducing the likelihood of cognitive dissonance and thus decreasing the probability of returns. This integrated approach to shopping ensures that multichannel consumers have a complete understanding of what they are purchasing, leading to lower return rates as their purchases are based on a more informed and confident assessment. Therefore, in our second hypothesis, we conjecture that:

Hypothesis 2 (**H2**): Multichannel consumers are (a) more (b) less likely to return a product than single-channel consumers post-purchase.

Based on the theoretical grounding so far in Section 3, we present the final hypothesis regarding the mediating role of product attributes (i.e., niche and experience levels) in the relationship between consumers' multichannel usage and their return likelihood. Formally, we hypothesize that:

Hypothesis 3 (**H3**): Niche and experience products in parallel mediates the relationship between multichannel usage and return likelihood, such that multichannel consumers exhibit higher return likelihood through a higher tendency to purchase niche and experience products compared to their single-channel counterparts.

4. Data and Model

In this section, we first describe our panel data in Section 4.1 and how it is ideal for achieving the objective of the study. We then present in Section 4.2 the definitions of our variables and their descriptive statistics. Last, we specify the base econometric model and discuss our identification strategy in Section 4.3.

4.1. Data Description

We obtained a detailed transaction panel data from a large furniture retailer in a European country. The retailer sells *identical* product assortment through three sales channels–online, showroom, and catalog, and refreshes the assortment every three months. In the *online* store, consumers can search for product information and place their orders through the company's web portal. They can also visit one of 36 physical *showroom* stores operated by the retailer across the country. In the stores, consumers can experience the products to obtain tactile information. Moreover, with the carefully assembled exhibits, they can visualize product placements in their homes and be more informed to evaluate the actual utility of the product. They can also consult the store associates with their purchases. Note that as opposed to the traditional brick-and-mortar stores that carry inventory, these showroom stores do not carry inventory. Therefore, all in-store purchases must be delivered to the consumers or picked up from a warehouse by the consumers themselves. Last, consumers can also search for product information on the *catalog* and place the orders by phone. The consumers receive a new catalog every three months in their mailboxes.

Our data comprise 406,082 transactions that occurred during the entire catalog season from January 01, 2015 to March 31, 2015 (hereafter, the focal period). These transactions occurred across three different channels: online, showroom, and catalog. For each transaction, we observe the transaction date and identification (ID), customer ID, stock-keeping unit (SKU), product description, quantity purchased for each SKU, and SKU price. Additionally, we have data on which channel the order was received through, the method of fulfillment chosen by the consumer (delivery or pick up from the warehouse), and whether the consumer returned any SKUs after the purchase. We note that the retailer has a uniform return policy across all three channels. Consumers have the option to return the product by bringing it back to the showroom or warehouse themselves, or they can arrange for a pick-up service provided by the retailer. If the pick-up service is chosen, consumers are charged a fixed return fee based on their regional location. In both cases, the cost of returning the products is the responsibility of the consumers. Furthermore, consumers have a 14-day window from the time the products are picked up from the warehouse or delivered to their address to return the product for a full refund or replacement. They are not required to provide a valid reason for returning the products, but they must provide proof of purchase or a receipt.

We excluded instances where consumers transacted only a single purchase during our focal period so that we can obtain more reliable estimates from our econometric model, unbiased by spurious behavioral effects. This represents 27.4% (or 111,345) of the observations.[1] In addition, we removed transactions of customized products as these products naturally have a much lower likelihood of being returned. Since we do not directly observe which SKUs are customized, we infer based on fulfillment lead times that exceeded 300 days, following our interview with a senior store manager. This constitutes 389 observations. Consequently, our final sample consists of a total of 294,348 observations.

We emphasize that all three channels provide not only the same product assortment during the focal period, but also the same modes of order fulfillment and product prices. The retailer has a centralized system for fulfilling orders, which means that customers from any channel must first place their orders through that specific channel. Afterward, they can choose to have their orders delivered to them or pick them up from a warehouse. Consistent with Brynjolfsson et al. (2011), by focusing our analysis on one catalog season (i.e., a quarter), we can control for product assortment.

[1] The results are qualitatively consistent even if the full sample is used.

In turn, our data are ideal to contrast the return behavior of single-channel consumers who use a single channel such as the online, showroom, or catalog channel with multichannel consumers who employ more than one channel (e.g., online and showroom, or showroom and catalog) for their purchases with the focal retailer.

We note that although our panel is relatively short and therefore does not allow us to observe all consumers' actual channel adoption behavior, for example, whether a consumer first adopted the online channel and then the showroom channel for her purchases, the benefits gained from our focal period that maintains the same assortment, pricing, and fulfillment modes outweigh this limitation so that we can properly examine consumers' return behavior in a relatively "clean" setting that is unconfounded by supply-side differences across the channels. However, we do observe a sample of consumers' actual channel adoption sequence that occurred during our period of analysis. Moreover, we have access to accurate classification data of whether a consumer is a multichannel user or a single-channel user. This is necessary for the core analyses in this paper. Therefore, for the analyses in Sections 6.3 and 7.3, we conduct the examination based on the sample of consumers which we do observe their channel adoption sequence, if any. Moreover, our context involving the retailing of furniture products provides an ideal setup to test our hypotheses. Furniture is representative of a non-digital product, and involves varying levels of uncertainty regarding information such as quality and fit across different sales channels (Ofek et al. 2011). The retailer in our study offers a consistent range of 20 product categories across all three channels. These categories include bathroom, bed, bedroom, bedside, bedsprings, bookcase, bridge, chair, chest, column, couch and sofa, dresser, kitchen, living room, mattress, mirror, office, showcase, table, and wardrobe. This diverse product range allows us to analyze and compare items based on their experiential nature (e.g., couch) versus search-oriented attributes (e.g., mirror), as well as their popularity (e.g., table) or specialization/nicheness (e.g., chest).

4.2. Variable Definitions

Table 1 presents the definitions of the key variables. The average product return rate in our sample is 4% and each SKU contributes approximately 0.76% of the total sales volume in each of the three channels. The average price per SKU is EUR 226.95 and the vast majority of the SKU transactions are fulfilled by home delivery ($1 - 0.13 = 0.87$) as opposed to warehouse pickup. On average, consumers are located 23 km and 19 km apart from the fulfillment warehouse and showroom store, respectively. Each consumer made an average of four transactions during the focal period.

Table 2 further shows the return rate and number of observations across the three channels, separately. The average return rate is 4% in the showroom channel, somewhat lower compared to 5% ($\triangle = 0.04 - 0.05 = 0.01$, $p = 0.00$) and 7% ($\triangle = 0.04 - 0.07 = –0.03$, $p = 0.00$) in the

Table 1: Definition of Variable and Descriptive Statistics

Type	Variable	Description	Min	Max	Mean	Std. Dev.
Dependent Variable	Return ($RETURN_{ijt}$)	An indicator whether SKU i purchased by consumer j was returned in week t, 1 = yes, and 0 otherwise.	0.00	1.00	0.04	0.19
Independent Variable	Channel ($CHANNEL_{ij}$)	A categorical variable indicating the transacting channel for SKU i by consumer j in week t, o = Online, s = Showroom, and c = Catalog.	–	–	–	–
	Multichannel Consumer ($MULTICH_j$)	An indicator that equals 1 if consumer j uses more than one sales channels for their purchases during the focal period prior to an instance of product return, and 0 otherwise.[a]	0.00	1.00	0.06	0.24
Control Variables	Total Volume ($VOLUME_i$)	Percentage sales volume contribution by SKU i in the channel that received the transaction.	0.00	4.90	0.76	0.87
	Fulfillment Mode ($FULFILMODE_{ij}$)	An indicator of whether consumer j chose to fulfill SKU i to a warehouse for pick up (warehouse pickup) or to a ZIP code (home delivery), 1 = warehouse pick up, and 0 otherwise. Consumers can only choose one fulfillment mode regardless of the quantity of the SKU in a purchase.	0.00	1.00	0.13	0.33
	Distance between Warehouse and Consumer Location ($DISTWC_j$)	Great-circle distance (in km) separating the fulfillment warehouse and consumer j's ZIP code.	0.00	463.74	23.02	21.67
	Distance between Showroom Store and Consumer Location ($DISTSC_j$)	Great-circle distance (in km) separating the nearest showroom store and consumer j's ZIP code. For transactions that occurred in the showroom store, we compute the great-circle distance separating the store that received the transaction and consumer j's ZIP code.	0.01	298.56	19.42	20.66
	Purchase Frequency ($FREQUENCY_j$)	Count of purchase visits by consumer j during the sample focal period.	2.00	96.00	4.30	3.35
	SKU Price ($PRICE_i$)	Average price of SKU i during the focal period.	28	980.00	226.95	173.29
Fixed Effects	Product Category Factor ($PRODUCTCAT_{n,i}$)	A set of dummy variables, one for each of the 20 product categories to account for time-invariant product category characteristics (e.g., bulkiness). For example, $PRODUCTCAT_{1,i} = 1$ if SKU i belongs to product category 1, and 0 otherwise.	–	–	–	–
	Week Factor ($WEEK_t$)	A set of dummy variables, one for each of the 13 weeks to account for seasonality effects and temporal shocks.	–	–	–	–

Notes. [a] We define the variable this way to avoid the reverse causation issue in the empirical analysis; that is, a single-channel consumer becomes a multichannel consumer after experiencing a product return. Note that the classification of consumer type is provided by the company and uses only sales data and not the return data.

online and catalog channel, respectively. This observation is consistent even if we divide the sample into the two consumer types (i.e., single-channel vs. multichannel). The showroom is the primary sales channel, accounting for around 90% of all SKU orders. Moreover, contrasting multichannel consumers, single-channel consumers appear to consistently generate lower return rates in the online (0.048 vs. 0.073, $\triangle$ = –0.025, p = 0.00), showroom (0.037 vs. 0.041, $\triangle$ = –0.004, p = 0.00), and catalog (0.072 vs. 0.093, $\triangle$ = –0.021, p = 0.00) channels. The model-free evidence supports our hypothesis that multichannel consumers have a higher return rate than single-channel consumers. Nevertheless, this evidence is preliminary as it does not account for other factors that could potentially influence consumers' return behavior, such as product price. In Section 4.3, we address this issue by employing an econometric model and an identification strategy.

Table 2: Channel-Level Descriptive Statistics

	Channel	Min	Max	Mean	Std. Dev
Return Rate	Online	0.00	1.00	0.051	0.221
(*Overall*)	Showroom	0.00	1.00	0.037	0.189
	Catalog	0.00	1.00	0.074	0.262
Return Rate	Online	0.00	1.00	0.048	0.215
(*Single-Channel*	Showroom	0.00	1.00	0.037	0.189
Consumers)	Catalog	0.00	1.00	0.072	0.258
Return Rate	Online	0.00	1.00	0.073	0.260
(*Multichannel*	Showroom	0.00	1.00	0.041	0.198
Consumers)	Catalog	0.00	1.00	0.093	0.275
Number of Observations	Online	8,956 (3.04% of all orders)			
	Showroom	265,739 (90.28%)			
	Catalog	19,653 (6.68%)			
	Sample Total	294,348			
Number of Observations	Online	7,830 (2.87% of all orders by single-channel consumers)			
(*Single-Channel*	Showroom	250,080 (91.69%)			
Consumers)	Catalog	14,828 (5.44%)			
	Sample Total	272,738			
Number of Observations	Online	1,126 (5.21% of all orders by multichannel consumers)			
(*Multichannel*	Showroom	15,659 (72.46%)			
Consumers)	Catalog	4,825 (22.33%)			
	Sample Total	21,610			

4.3. Empirical Modeling and Identification

To formally conduct our analysis, we model the status of product return conditional on a purchase as a logistic specification. We set $RETURN_{ij} = 1$ if SKU i purchased by consumer j was returned in week t, and 0 otherwise. Then, $Pr(RETURN = 1 \setminus \mathbf{x} = \Lambda(\mathbf{x}\beta))$, where

$$\Lambda(\mathbf{x}\beta) = \frac{exp(\mathbf{x}\beta)}{1 + exp(\mathbf{x}\beta)}. \tag{1}$$

The vector $\mathbf{x}$ includes the set of variables in Table 1 and a constant. We specify the equivalent econometric model for estimation as

$$\begin{aligned} Logit(RETURN_{ijt} = 1) = \beta_0 + \psi_j + \gamma_k CHANNEL_{ijt} + \boldsymbol{CONTROLS_{ij}} \cdot \beta_2 + \\ \sum_n PRODUCTCAT_n \cdot \theta_{n,i} + \sum_t WEEK_t \cdot \omega_t + \varepsilon_{ij}, \end{aligned} \tag{2}$$

where ψ_j is the individual-specific effects that measure unobserved heterogeneity and ε is independent and identically distributed (i.i.d.) error term. For all model estimations, we denote channel $k = s$ (showroom) as the base. Therefore, γ_o and γ_c capture the return rate in the online and catalog channel, relative to the showroom channel, respectively. A positive and statistically significant coefficient would imply that the focal channel has a higher return rate compared to that of the showroom channel. Our primary identification strategy is to include an extensive list of fixed effects and control variables in our model that may influence consumers' return rate other than channel effects. These include consumer, product category and week fixed effects to control for unobserved consumer heterogeneity, product heterogeneity across categories (e.g., tables, mirrors), as well as time trends and seasonality effects. Including these fixed effects allows us to compare similar product categories sold to consumers during the same week across channels. Moreover, we include in the model the list of control variables ($CONTROLS$) in Table 1. Last, we incorporate cluster robust standard errors at the consumer province level in all of our analyses to allow for heteroskedasticity across observations within the consumer clusters.

5. Results

We first present a modified version of Model 2 to test H1 and the corresponding estimation results in Section 5.1. Although we stated P1–P4 as propositions based on existing theories and empirical findings from the literature, we conducted the empirical tests to confirm understanding in our context of interest. These results, which are all consistent with our understanding, are available in Online Appendix A. Second, we present the results to test H2 in Section 5.2 by estimating the likelihood of return between the two consumer types (single-channel and multichannel consumers). Finally, we present the parallel mediation analysis to test H3 in Section 5.3. This analysis aims to confirm the mediating role of product attributes (niche and experience levels) in the relationship between multichannel usage and return likelihood.

5.1. Return Behavior Analysis

To test H1, we implement a variation of Model 2. Specifically, we include a $MULTICH$ indicator and replace the product category fixed effects with SKU fixed effects so that the model is specified as

$$Logit(RETURN_{ijt} = 1) = \beta_0 + \psi_j + \gamma_k CHANNEL_{ijt} + \beta_1 MULTICH_j + \boldsymbol{CONTROLS_{ij}} \cdot \beta_2 + \sum_i SKU_i \cdot \theta_i + \sum_t WEEK_t \cdot \omega_t + \varepsilon_{ij}, \tag{3}$$

where SKU is an indicator, one for each of the 689 SKUs in our sample. The term β_1 is our coefficient of interest. If β_1 turns out to be nonsignificant in this specification given that we explicitly control for SKU fixed effects, then the finding reported in the extant literature citing differences in the return rate of multichannel versus single-channel consumers may in fact be driven by differences in the attributes of the products purchased by the two consumer groups. This provides a new mechanism based on product attributes in addition to informational differences across channels as well documented in the literature. This result also allows us to validate H1.

We provide the results of Model 3 in Table 3. In Column 1, we exclude the $MULTICH$ indicator, SKU and week fixed effects. In Column 2, we include the $MULTICH$ indicator and week fixed effects. We then add the SKU fixed effects in Column 3. We first interpret the results in Column 2. Without controlling product effects, multichannel consumers appear to exhibit lower return likelikehood ($\beta_1 = -0.597$, $p < 0.01$), which is consistent with the information search improvement explanation in Sections 3.1 and 3.4.

Next, we interpret the results in Column 3 given the full specification and lower log likelihood. As we expected, the β_1 coefficient is nonsignificant (0.065, $p = 0.247$); therefore, H1 is supported.[2] Importantly, the relationship observed in Column (2) fades away once we account for product characteristics. This suggests that differences in return rates among the two consumer groups become less significant after controlling for individual product effects, implying product attributes as a potential mechanism governing the relationship between consumers' multichannel usage and their return behaviors. We examine two of such attributes namely–product nicheness and product experience level as potential mechanisms in the next two sections.

Table 3: Return Behavior with SKU Controls

Variable	(1) Model 3	(2) Model 3	(3) Model 3†
$ONLINE$	0.856*** (0.167)	0.799*** (0.170)	0.505*** (0.083)
$CATALOG$	1.358*** (0.116)	1.252*** (0.112)	0.871*** (0.055)
$MULTICH$		–0.597** (0.221)	0.065 (0.056)
Control variables			
$\ln VOLUME$	–0.078*** (0.013)	–0.078*** (0.013)	0.060 (0.052)
$FULFILMODE$	0.393** (0.124)	0.391** (0.125)	0.263*** (0.073)
$\ln DISTWC$	–0.071 (0.088)	–0.072 (0.089)	–0.054 (0.048)
$\ln DISTSC$	–0.148* (0.069)	–0.155* (0.069)	–0.088* (0.039)
$\ln FREQUENCY$	0.418*** (0.121)	0.387** (0.120)	0.393*** (0.039)
$\ln PRICE$	0.072** (0.023)	0.072** (0.023)	
SKU Effects	No	No	Yes
Week Effects	No	Yes	Yes
Consumer Effects	Yes	Yes	Yes
No. of Observations	294,348	294,348	294,348
Log Likelihood	–34,582.22	–34,547.40	–34,266.56

Notes. Cluster robust standard errors are reported in parentheses.
† The estimation function is not concave when both $\ln PRICE$ and SKU fixed effects are included in the model. Therefore, we excluded $\ln PRICE$.
* p < 0.05, ** p < 0.01, *** p < 0.001.

5.2. Return Likelihood of Single-Channel vs. Multichannel Consumers

Given we have theoretically established in Sections 3.2 and 3.3 the understanding that multichannel consumers are more likely to purchase niche and experience products relative to single-channel consumers and that these products have higher post-purchase return likelihood, we now proceed to formally test our second hypothesis, H2, to determine whether multichannel consumers indeed have a higher product-return propensity than single-channel consumers. To do so, we implement a sub-sample analysis based on Model 2 at the consumer type level (i.e., single-channel vs. multichannel

[2] We note, however, that failing to reject a null hypotheses does not absolutely mean that the relationship is absent. However, as we see in Column (2) of Table 3, without controlling for SKU effects, $MULTICH$ does have a negative and statistically significant impact on the return probability.

consumers). Larger coefficients for β_0, γ_o, and γ_c in one consumer type would suggest a higher return propensity than the other consumer type. We present the estimates in Table 4. As the results show, not only do multichannel consumers exhibit a higher return odds than single-channel consumers in the showroom ($\beta_0 = 0.01$ $[exp(-4.30)]$ vs. 0.001 $[exp(-6.885])$, $p < 0.001$) channel, the former also have a higher odds of returning products than the latter in the online ($\gamma_o = 0.02$ $[exp(-4.304 + 0.509)]$ vs. 0.002 $[exp(-6.885 + 0.919)]$, $p < 0.001$) and catalog ($\gamma_c = 0.04$ $[exp(-4.304 + 1.036)]$ vs. 0.004 $[exp(-6.885 + 1.457)]$, $p < 0.001$) channel. These results support H2(a), that is, multichannel consumers are more likely to return a product than single-channel consumers post-purchase.

Table 4: Return Behavior

Variable	(1) Model 2 for single-channel consumers	(2) Model 2 for multichannel consumers	(3) Model 2 for full sample
ONLINE	0.919*** (0.184)	0.509* (0.236)	0.767*** (0.171)
CATALOG	1.457*** (0.133)	1.036*** (0.137)	1.272*** (0.113)
MULTICH			0.603*** (0.107)
Control variables			
ln*VOLUME*	–0.098*** (0.017)	–0.100 (0.058)	–0.099*** (0.015)
FULFILMODE	0.330** (0.127)	0.789*** (0.184)	0.361*** (0.123)
ln*DISTWC*	–0.109 (0.094)	0.146 (0.118)	–0.074 (0.088)
ln*DISTSC*	–0.157* (0.073)	–0.252** (0.085)	–0.159* (0.069)
ln*FREQUENCY*	0.543*** (0.142)	0.035 (0.142)	0.450*** (0.124)
ln*PRICE*	0.063 (0.042)	0.006 (0.094)	0.051 (0.036)
Constant	–6.885 (0.331)	–4.304*** (0.650)	–6.748*** (0.286)
Product Category Effects	Yes	Yes	Yes
Week Effects	Yes	Yes	Yes
Consumer Effects	Yes	Yes	Yes
No. of Observations	272,738	21,610	294,348
Log Likelihood	–30,674.06	–3,654.42	–34,359.55

Notes. Cluster robust standard errors are reported in parentheses.
* p < 0.05, ** p < 0.01, *** p < 0.001.

5.3. Parallel Mediation Analysis

To test H3, we conduct a regression-based mediation analysis with nonparametric bootstapping approach to reliably estimate the mediation effects with adequate statistical power (Hayes 2018). We use 10,000 bootstrap resamples for the analysis. Consistent with the previous analyses, we include the $CHANNEL$ variable, the control variables and the fixed effects in Table 1 for this analysis to enhance the statistical power and precision of the estimates (Preacher and Hayes 2008).

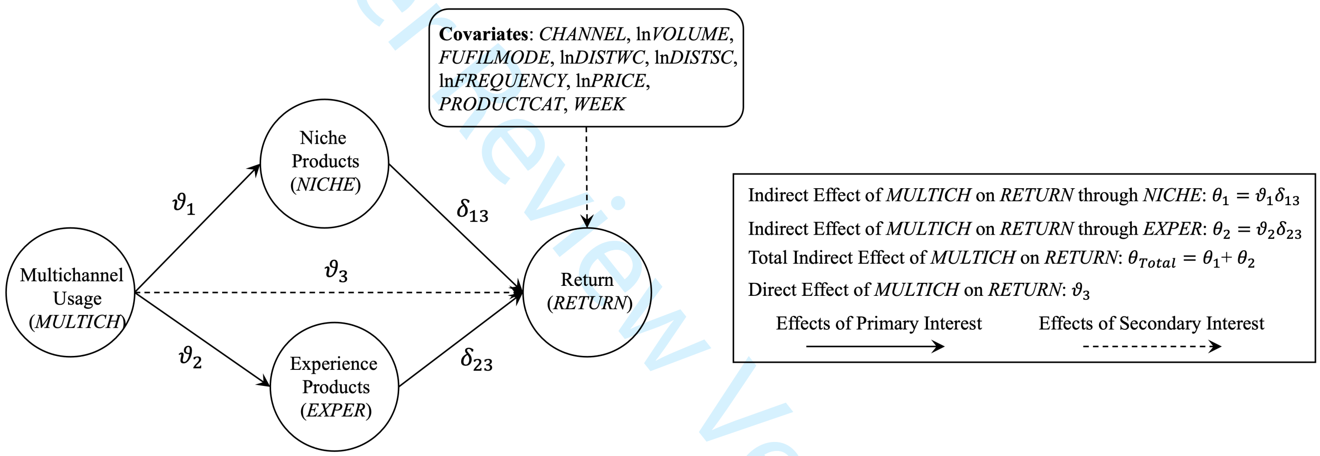
Table 5 presents the results of the analysis. It includes the estimated individual path coefficients, direct effects, total indirect effects, along with the path-specific indirect effects with 95% percentile-based bootstrap confidence intervals (CIs). Figure 2 provides a visualization of the mediation effects and notations to faciliate discussion. A significant mediation effect exists when the CI for the estimate of an indirect effect does not contain zero. The results support H3. Specifically, niche ($\theta_1 = \vartheta_1\delta_{13} = 0.720$, CI = = [0.359, 1.080]) and experience ($\theta_2 = \vartheta_2\delta_{23} = 1.018$, CI = [0.484, 1.552]) product attributes *fully* mediate the relationship between multichannel usage and the likelihood of a product being returned. This is evidenced by the statistically nonsignificant direct effect of $MULTICH$ on $RETURN$ ($\vartheta_3 = 0.062$, CI = [–0.068, 0.192]), in which the CI includes zero. Furthermore, the total indirect effect of $MULTICH$ on $RETURN$ is 1.738 and statistically significant ($\theta_{total} = \theta_1 + \theta_2 = \vartheta_1\delta_{13} + \vartheta_2\delta_{23} = 1.738$, CI = [1.033, 2.443]).

Table 5: Parallel Mediation Analysis

Variable	Direct effects [CI]	Total indirect effect [CI]	Mediation paths/subpaths with effect sizes	Indirect effects	95% CIs
$MULTICH$	0.062 [–0.068, 0.192]	1.738 [1.033, 2.443]	$MULTICH \xrightarrow{2.571} NICHE \xrightarrow{0.280} RETURN$	0.720	[0.359, 1.080]
			$MULTICH \xrightarrow{0.975} EXPER \xrightarrow{1.044} RETURN$	1.018	[0.484, 1.552]

Notes. CI denotes 95% percentile-based bootstrap confidence interval, $MULTICH$, $NICHE$, $EXPER$, and $RETURN$ denote multichannel consumers, niche products, experience products, and return indicator, respectively. Covariates: $CHANNEL$, $\ln VOLUME$, $FULFILMODE$, $\ln DISTWC$, $\ln DISTSC$, $\ln FREQUENCY$, $\ln PRICE$, $PRODUCTCAT$, and $WEEK$.

Figure 2: Statistical diagram and notations for mediation analysis



6. Robustness

We provide three alternative specifications to further demonstrate the robustness of our estimates based on a full sample analysis (Section 6.1), a Heckman selection and control function analysis (Section 6.2), and a risk-set matching analysis (Section 6.3).

6.1. Full Sample Analysis

We estimate the coefficients using the full sample rather than split it into the two consumer groups. In other words, we employ Model 2 and include an indicator, where $MULTICH = 1$ and $MULTICH = 0$, to denote multichannel and single-channel consumers, respectively, and re-estimate the model. A positive and statistically significant coefficient for $MULTICH$ would indicate that multichannel consumers have a higher odds to return products post-purchase than single-channel consumers. Indeed, we observe in Column 3 of Table 4 that the coefficient is positive and statistically significant (0.603, $p < 0.001$), which is consistent with our earlier finding derived from Columns 1 and 2 in the same table.

6.2. Heckman Selection and Control Function Analysis

In our main models, we incorporate a wide range of fixed effects and control variables. However, there is a possibility of channel-selection bias. This means that if consumers with a tendency for lower returns choose to primarily shop at the showroom over the other two channels, it could artificially inflate our estimation coefficients. Moreover, the estimates may suffer from endogeneity issues such as omitted variable bias associated with the $MULTICH$ indicator. We note that we mitigated the concern of reversal causality by operationalizing $MULTICH$ based on consumers' channel usage prior to their experiencing the first product return. As such, the variable is constructed based on purchasing behavior before the outcome (i.e., product return) is observed.

To alleviate the channel-selection bias, we adopt a Heckman selection method (Heckman 1976, 1979) as an alternative specification. We specify a first-stage multinomial Logit model of channel selection to compute the channel-specific correction term ratio (λ) and then include the term λ in each of the model in Tables 3, 4, and 5. Details of the model are provided in Online Appendix B.

Next, we introduce an instrument for $MULTICH$ that is constructed based on the proportion of multichannel consumers (excluding the focal consumer) in the same ZIP code as the focal consumer. We motivate the relevance of this instrument based on the concept of homophily or social influence (Ma et al. 2015). The basic idea is that consumers who are close together (e.g., in the same neighborhood, social network, or ZIP code) are more likely to behave similarly or exhibit similar purchasing behavior. The instrument satisfies the exclusion restriction condition as the share of multichannel consumers in the ZIP code does not directly influence the tendency of the focal consumer to return a product. We provide additional details regarding the validity of the instrument (satisfying both the relevance and exclusion restriction condition) in Online Appendix B. We use this instrument in the control function approach (Wooldridge 2015) which estimates a residual term and include it in each of the model in Tables 3, 4, and 5. Armed with both the λ from the Heckman selection process and the residual term from the control function, we reestimate the regressions. The full results are provided in the same online appendix. The estimates in Tables B.2, B.3, and B.4 are all qualitatively consistent with those reported in Tables 3, 4, and 5, thereby, providing further assurance of our main findings.

6.3. Risk-set Matching Analysis

Hitherto, although we implemented fixed-effect regressions with an extensive set of controls and fixed effects and show robustness of our results even after implementing the analysis using the full sample and incorporating Heckman selection method, we did not account for consumers' higher propensity to gravitate toward using multiple channels in their purchasing due to more intense consumption trajectory. To address this issue, we adopt the risk-set matching procedure in Bell et al.

(2020) to implement a matching procedure that compare the evolution of pairs of multi-channel (treated) and single-channel (control) consumers that share similar consumption trajectories prior to the former's first use of a second channel. This approach provides better support for a causal interpretation of the return effect based on exposure to the multiple channels.

The procedure creates pairs of "identical" consumers based on similar observable characteristics. To ensure proper comparison, these pairs are formed in a way that treatment and control consumers share similarity before treatment (i.e., first usage of a second channel), considering that treatment consumers can adopt a second channel at different time points. In risk-set matching, a newly treated consumer at time t is matched with one or more control consumers not yet treated at the same time t. We match consumers who receive treatment at time t (i.e., first use of a second channel at time t) with consumers who had the same treatment probability at time t, meaning they had the same hazard rate, but opted not to adopt a second channel. This way, we prevent any potential bias in our comparison of the outcomes of interest that could arise if a control consumer were to use a second channel at a later time.

We consider consumer characteristics and variables that summarize the purchasing trajectory of a consumer. These variables can change over time and are used in the matching process. We use several variables that have shown to be influential in consumers' choice of sales channel for matching consumer j before time t. Consistent with Bell et al. (2020), these variables include the total number of transactions, the time since last purchase, the total dollar sales, the total number of unique subcategories purchased, and the distance from consumer j's ZIP code to the nearest showroom store at time t. Following the approach by Rosenbaum et al. (2010), we do not restrict a control consumer to be matched with only one treatment consumer. We use a nearest neighbor matching method with Mahalanobis distance based on the five covariates mentioned earlier. The matching is done on a 1:1 basis between treated and control consumers. We also considered several other matching alternatives; our results remain consistent across different combinations of matched units (i.e., number of matches per treated unit) and distance metrics.

For the analysis, we use only the pool of consumers whom we observe their actual channel adoption sequence, in the case of adopting an additional channel, if any. We retain 3,794 consumers: from 1,897 treatment consumers who used a second channel for their purchases and the corresponding best match for each treatment consumer from the pool of control consumers who maintained as single-channel consumers. The results in Table C.1 of Online Appendix C demonstrate that the matching procedure was effective in creating treatment and control groups that are virtually identical to each other across the set of matching covariates. With the matched sample, we compare the return rates ($RETURNRATE$) of the treated consumers versus the control consumers. $RETURNRATE$ measures the number of returns divided by the total number of transactions for each consumer. Relative to with their matched control counterpart, the results in Table C.2 of Online Appendix C show that treated consumers generate an average of 2.7% more returns over their subsequent purchase history following their first usage of a second channel ($p < 0.001$). Overall, these results are consistent with the results in Table 4.

7. Post Hoc Analysis

In this section, we implement a online experiment in Section 7.1 to gain a deeper understanding of why multichannel consumers purchase more niche and experience products compared to their single-channel counterparts. Moreover, we implement a series of post hoc analysis to explore the managerial implications of the findings reported in Section 5. Specifically, we analyze which channel the focal retailer should use to distribute niche and experience products (Section 7.2), and shed light on the value of serving multichannel consumers given their higher return rates (Section 7.3).

7.1. Online Experiment: Effect of Multichannel Usage on Consumers' Confidence and Willingness to Purchase Niche and Experience Products

To provide direct evidence of our conjecture of why multichannel consumers are more likely to purchase niche and experience products than single-channel consumers, we design an online experiment. We posit that this is because having access to multiple channels for purchasing a product makes these consumers feel more confident about their ability to make right product decisions (Bearden et al. 2001). That is, multichannel consumers feel more capable of evaluating the attributes and quality of less familiar or more experiential products. The increased confidence leads these consumers to be more adventurous in their purchasing habits, venturing beyond popular and search items to explore the less popular and more experiential ones (Balasubramanian et al. 2005). Goldsmith and Hofacker (1991) term this behavior *consumer innovativeness*.

We create a hypothetical online shopping scenario for a lounge chair. We invite 300 individuals from Amazon Mechanical Turk to respond to a series of questions. The participants are randomly divided into two groups: multichannel or single-channel condition. The multichannel group is informed that they can access the physical showroom, online platform, and catalog channels, while the single-channel group is informed that they can only access the online platform. We control for the participants' age, education level, gender, past lounge-chair shopping experience, and experiment duration. We provide further details about the experiment in Online Appendix D.

Column 1 in Table 6 conducts a manipulation check. The coefficient of the single-channel condition is negative and statistically signficant, suggesting that participants with access to only the online channel are approximately 11% less confident about their purchase decisions. Interestingly, based on the coefficient in Column 2 of the same table, we find that participants with access to multiple channels appear to have a higher willingness to try new products. The results in Columns

3 and 4 further show that participants with access to all the three channels are approximately 15% and 18% more willing to purchase a niche or an experience product, respectively.

Table 6: Effect of Multichannel Usage on Willingness to Purchase Niche and Experience Product

Variable	(1) Perceived Confidence	(2) WTP New Product	(3) WTP Niche Product	(4) WTP Experience Product
$SINGLECHANNEL$	–11.22*** (2.36)			
$PURCHASECONFIDENCE$		26.55*** (5.87)	15.31*** (3.12)	18.22*** (4.27)
Controls	Yes	Yes	Yes	Yes
No. of Observations	290	290	290	290
R^2	0.425	0.464	0.467	0.442

Notes. * p < 0.05, ** p < 0.01, *** p < 0.001.

7.2. Which Channel to Use for Distributing Niche and Experience Products?

We examine which sales channel should the retailer use to distribute niche and experience products. A consumer prefers transacting in a sales channel that provides the highest utility. Therefore, let the preference utility U of consumer j purchasing SKU i from channel k be

$$\begin{aligned} U_{ijk} = {} & \beta_0 + \psi_j + \beta_1 MULTICH_j + \beta_2 \ln NICHENESS_{ik} + \beta_3 \ln EXPERIENCE_i + \beta_4 \ln VOLUME_i + \\ & \beta_5 \ln PRICE_i + \boldsymbol{DEMOGRAPHIC_j} \cdot \beta_6 + \boldsymbol{DEMOGRAPHIC_j} \times \ln NICHENESS_{ik} \cdot \beta_7 + \\ & \boldsymbol{DEMOGRAPHIC_j} \times \ln EXPERIENCE_i \cdot \beta_8 + \boldsymbol{CONTROLS_{ij}} \cdot \beta_9 + \\ & \boldsymbol{CONTROLS_{ij}} \times \ln NICHENESS_{ik} \cdot \beta_{10} + \boldsymbol{CONTROLS_{ij}} \times \ln EXPERIENCE_i \cdot \beta_{11} + \\ & \sum_n PRODUCTCAT_n \cdot \theta_{n,i} + \sum_t WEEK_t \cdot \omega_t + \epsilon_{ijk}, \end{aligned} \tag{4}$$

where $DEMOGRAPHIC$ is a vector of ZIP code level demographic attributes to capture consumer characteristics, including the average age of household head (AGE), the average percentage of population with university degree qualification ($EDUCATION$), the average number of members in household ($HOUSEHOLDSIZE$), and the percentage of home ownership as opposed to being leased ($HOMEOWNERSHIP$). These variables are known to influence channel choice (Fox et al. 2004, Lim et al. 2024, Bhatnagar and Ratchford 2004). The vector $CONTROLS$ comprises the remaining control variables in Table 1, namely–$FULFILMODE$, $DISTWC$, $DISTSC$, and $FREQUENCY$. The term ϵ is a normally distributed random error component. All remaining terms are defined as before. We set channel $k = s$ (showroom) as our base. We implement the analysis by specifying a multinomial Probit choice model for the probability of channel preference (P) using the following equation:

$$P_{ijk} = \int_{-\infty}^{V_{ijk}} \int_{-\infty}^{V_{ijk-1}} \Phi(\varepsilon_{ijk}, ..., \varepsilon_{ijk-1}) d\varepsilon_{ijk}, ..., d\varepsilon_{ijk-1}, \tag{5}$$

where Φ is the probability density function of normal distribution and V is the deterministic component of utility. We perform randomly sampled five-fold cross-validation to evaluate the model.

We evaluate the model using accuracy and AUC score. Our model achieves an average accuracy of 93% matches (i.e., the predicted channel by our choice model *matches* the observed channel in the holdout sample) and an AUC score of 0.91. As a technical note, either random guessing a channel or predicting all transactions in any given channel will give an AUC score of 0.33. We compute the AUC score for the validation sample of each fold and averaged across the five folds. These results show that our specified choice model has a high predictive accuracy. The full set of estimates of the choice model based on the entire sample is available in Online Appendix E. After ascertaining the performance of the model, we use the constructed model for channel prediction by spliting our full sample into 70% training data for estimation and use the remaining 30% as holdout data for out-of-sample prediction and estimate the impact on the overall return rate and the return rate of single-channel and multichannel consumers, separately.

Based on the estimates in Table 7, the average return rates are consistently *lower* when the predicted channel and the observed channel matches (Match = 1) than when they do not (Match = 0), for the overall holdout sample (0.038 vs. 0.066, $p < 0.001$), and across the single-channel (0.038 vs. 0.063, $p < 0.001$)) and multichannel (0.046 vs. 0.083, $p < 0.001$) consumer sub-samples.

Table 7: Predicted vs. Observed Channel Analysis on Return Rate

Match	Mean*	Std. Dev.	# of Observations
Overall			
Match = 0	0.066	0.243	6,197
Match = 1	0.038	0.192	82,107
Total	0.040	0.196	88,304
Single-Channel			
Match = 0	0.063	0.243	5,280
Match = 1	0.038	0.190	76,541
Sub-Total	0.039	0.194	81,821
Multichannel			
Match = 0	0.083	0.276	917
Match = 1	0.046	0.211	5,567
Sub-Total	0.052	0.222	6,484

Notes. *Mean and Std. Dev. denote average return rate and standard deviation, respectively.

We then repeat the procedure and conduct two additional analyses to examine whether these results hold when we implement the estimation at the product type level, that is, niche versus popular products, and experience versus search products. To do so, for the first analysis, we divide the holdout sample into niche and popular products at the sample median, which is 193, from a range of 1 to 689 based on individual SKU's sales volume contribution. For the second analysis, we divide the holdout sample into experience and search products at the sample median, which is 3, from a range of 1 to 7. We provide these results in Tables 8a and 8b.

Based on the results Table 8a, we continue to see that the average return rates are lower when the predicted channel from our choice model matches that of the observed channel across the three sample categories (overall, single-channel, and multichannel) and between popular and niche products. Moreover, these findings continue to hold when we examine the estimates in Table 8b comparing experience versus search products. All pair-wise mean differences (i.e., Match = 1 vs. Match = 0) are statistically significant at the 0.05 level.

Given the above results showing that the retailer experiences lower return rates for products that are distributed via the channel predicted by our choice model and together with the estimates in Table E.1 of Online Appendix E, we propose that the retailer should feature niche ($\beta_2 = -0.012$, $p = 0.05$ for online and $\beta_2 = -0.779$, $p < 0.001$ for catalog) and experience ($\beta_3 = -0.440$, $p = 0.05$ for online and $\beta_3 = -1.826$, $p < 0.001$ for catalog) products in the showroom channel and popular and search products in the online and/or catalog channel.

Table 8: Predicted vs. Observed Channel Analysis and Return Rate (Product Type Level)

Match	Mean*	Std. Dev.	# of Observations
Overall (Popular)			
Match = 0	0.053	0.224	1,774
Match = 1	0.036	0.187	42,121
Overall (Niche)			
Match = 0	0.071	0.257	4,422
Match = 1	0.040	0.197	39,987
Single-Channel (Popular)			
Match = 0	0.048	0.214	1,461
Match = 1	0.036	0.186	39,645
Single-Channel (Niche)			
Match = 0	0.069	0.253	3,819
Match = 1	0.039	0.194	36,896
Multichannel (Popular)			
Match = 0	0.076	0.266	315
Match = 1	0.039	0.194	2,476
Multichannel (Niche)			
Match = 0	0.087	0.282	603
Match = 1	0.052	0.223	3,090

(a) Niche vs. Popular Products

Match	Mean*	Std. Dev.	# of Observations
Overall (Search)			
Match = 0	0.060	0.238	2,169
Match = 1	0.036	0.187	36,630
Overall (Experience)			
Match = 0	0.069	0.254	4,028
Match = 1	0.040	0.196	45,477
Single-Channel (Search)			
Match = 0	0.059	0.235	1,889
Match = 1	0.036	0.186	34,027
Single-Channel (Experience)			
Match = 0	0.065	0.248	3,392
Match = 1	0.039	0.194	42,513
Multichannel (Search)			
Match = 0	0.071	0.256	281
Match = 1	0.041	0.199	2,602
Multichannel (Experience)			
Match = 0	0.089	0.285	637
Match = 1	0.051	0.220	2,964

(b) Experience vs. Search Products

Notes. *Mean and Std. Dev. denote average return rate and standard deviation, respectively. All pair-wise mean differences for each sample category-product type subsample (e.g., Overall (Popular) subsample comparing Match = 1 vs. Match = 0) are statistically significant at the 0.05 level.

7.3. Relative to Single-Channel Consumers, Do Multichannel Consumers Generate More Revenue for the Retailer?

So far, we have established the understanding that multichannel consumers exhibit a higher return likelihood than single-channel consumers across all the three channels. This is because the former tended to purchase more niche and experience products, and in turn, products with these attributes are more likely to be returned post-purchase. Consequently, we ask if there is economic value for the retailer to serve these consumers. To do so, we conduct two analyses. For the first analysis, we calculate the average total revenue in terms of expenditure (results in Column 4 of Table 9a) and the average revenue per transaction (Column 5) generated by a single-channel consumer versus a multichannel consumer using our full sample. Then, we compute the average lost in revenue due to returned products per consumer type (Column 6) and per transaction per consumer type (Column 7). We calculate revenue loss based on the price of the product. Last, we account for the lost in revenue by subtracting the total revenue by the revenue lost to arrive at the net revenue per consumer type (Column 8) and the net revenue per transaction per consumer type (Column 9). All calculations are in EUR. We implement this analysis at the channel level.

For the second analysis, we focus on the channel adoption behavior of multichannel consumers and examine the sequence of channel adoption that generates the largest marginal gain in revenue for the retailer. We rely on a sample of (multichannel) consumers which we observe their actual channel adoption sequence that occurred during the focal period for this investigation. We indicate the *primary* channel as the first channel the consumer uses to purchase products with the focal retailer.[3] We then identify the new channel the consumer used that first occurred during the focal period as the *second* channel.[4] We repeat the procedure as per the first analysis and include an additional column (Column 10 in Table 9b) that compute the percentage change (%$\triangle$) in the net revenue obtained per transaction per multichannel consumer when a second channel is adopted relative to the primary channel used by an average single-channel consumer. This way, we estimate the marginal gain in revenue when a consumer adopts a second channel. For example, if an initially single-channel consumer uses the online channel as the primary (first) channel for their purchases, this analysis will estimate the percentage increase in revenue when they adopt either the showroom or the catalog channel as the second channel and, in turn, becomes a multichannel consumer.

The results in Column 8 of Table 9a shows that after accounting for the lost in revenue due to the returned products, multichannel consumers, on average, generate a larger amount of revenue relative to single-channel consumers across the online (747.62 vs. 633.34 EUR), showroom (977.02 vs. 944.15 EUR), and catalog (1,431.58 vs. 620.22 EUR) channels. Moreover, although the former's basket value is also greater than the latter in the online (210.60 vs. 202.35 EUR) and catalog (271.65 vs. 182.42 EUR) channels, the basket value in the showroom channel is lower (172.01 vs. 220.59 EUR). This suggests that multichannel consumers may be purchasing either lower value items or fewer units per transaction compared to single-channel consumers. All pair-wise mean differences are statistically significant at the 0.05 level.

Furthermore, based on the estimates in Table 9b, although we observe that all channel-adoption pairs generate positive marginal revenue, the largest gains were obtained when consumers use either the online or catalog channel as the primary channel and then adopt the showroom as the second channel (Online/Catalog→Showroom). The former gains about 45% increase in marginal revenue whereas the latter gains approximately 39%. Overall, these findings suggest that the retailer attains the largest amount of marginal revenue when consumers move from a non-physical channel to a physical channel. We attribute this to the physical channel's ability, in this case, the showroom's

[3] We have access to this information from the focal retailer.

[4] Given there were only 164 consumers that used all three channels and the third channel has, on average, only been used at most twice per consumer in our sample, we do not include these observations in this analysis. Consequently, we dropped 628 observations from the analysis.

Table 9: Revenue Analysis

(a) Consumer Type

Channel	(1) # of Consumers	(2) Avg. # of Transactions	(3) Total Revenue (EUR)	(4) Avg. Spent per Consumer (EUR) [(3)/(1)]	(5) Avg. Spent per Transaction per Consumer (EUR) [(4)/(2)]	(6) Avg. Revenue Lost Due to Return per Consumer	(7) Avg. Revenue Lost Due to Return per Transaction per Consumer	(8) Net Revenue per Consumer [(4)–(6)]	(9) Net Revenue per Transaction per Consumer [(5)–(7)]
Single-Channel									
Online	3,031	3.13	2,031,545.37	670.25	214.14	36.90	11.79	633.34	202.35
Showroom	77,176	4.28	75,892,733.80	983.37	229.76	39.22	9.16	944.15	220.59
Catalog	5,559	3.4	3,739,024.06	672.61	197.82	52.39	15.41	620.22	182.42
Total	85,766	4.18	81,663,303.2	952.16	226.70	39.99	9.52	912.17	217.18
Multichannel									
Online	441	3.55	352,527.32	799.38	225.178	51.76	14.58	747.62	210.60
Showroom	4,674	5.68	4,791,611.37	1,025.16	180.49	48.14	8.47	977.02	172.01
Catalog	786	5.27	1,235,835.05	1,572.31	298.35	140.73	26.70	1,431.58	271.65
Total	5,901	5.47	6,379,973.74	1,081.17	196.57	60.74	11.04	1,020.43	185.53

(b) Primary-Second Channel

Channel Adoption Pair Primary→Second	(1) # of Consumers	(2) Avg. # of Transactions	(3) Total Revenue (EUR)	(4) Avg. Spent per Consumer (EUR) [(3)/(1)]	(5) Avg. Spent per Transaction per Consumer (EUR) [(4)/(2)]	(6) Avg. Revenue Lost Due to Return per Consumer	(7) Avg. Revenue Lost Due to Return per Transaction per Consumer	(8) Net Revenue per Consumer [(4)–(6)]	(9) Net Revenue per Transaction per Consumer [(5)–(7)]
Online→Showroom	430	2.80	373,180.31	867.86	309.95	68.03	24.29	799.83	285.65
Online→Catalog	11	4.36	13,133.00	1,193.91	273.83	82.45	18.91	1,111.45	254.92
Showroom→Online	2,375	3.63	2,663,625.26	1,121.52	308.96	45.04	12.41	1,076.48	296.55
Showroom→Catalog	2,299	4.05	2,712,148.69	1,179.71	291.28	77.24	19.07	1,102.46	272.21
Catalog→Online	549	2.54	338,173.16	615.98	242.51	30.88	12.15	585.10	230.34
Catalog→Showroom	237	4.29	279,713.31	1,180.22	275.11	112.96	26.33	1,067.26	248.78

(b) Primary-Second Channel (cont'd)

Channel Adoption Pair Primary→Second	(10) %△ $\left[\frac{\text{(5) of Table 9b–(5) of Table 9a}}{\text{(5) of Table 9a}}\right]$
Online→Showroom	44.74
Online→Catalog	27.87
Showroom→Online	34.47
Showroom→Catalog	26.78
Catalog→Online	22.59
Catalog→Showroom	39.07

ability to resolve information uncertainty about products, especially those with higher degree of nicheness and experiential level (Lim et al. 2024). These interpretations are consistent with the descriptive statistics in Table 2 and the results in Table 9a on the average lost revenue, which show that showroom generates not only the lowest return rate among the channels but also the least amount of revenue loss due to returned products than the online or catalog channel.

8. Conclusion

This research provides the first empirical documentation of a new mechanism clarifying the nuanced interplay between product attributes and multichannel usage and return behaviors. The commonly accepted knoweldge in the extant literature is that by leveraging multiple channels, consumers benefit from a reduction in product uncertainty, and the added shopping convenience leads to increases in sales revenue and a decreases in product return rates at the retailer stores. However, in our context involving products of different levels of consumer-involvement and information uncertainty, we find that consumers' multichannel shopping usage can lead to an increase in product return rates post-purchase. This is because, compared to single-channel consumers, multichannel shoppers tend to purchase niche and experience products and that these products have higher return likelihoods than their popular and search counterparts. Through an online experiment, we find direct evidence that having access to multiple channels increases consumers' confidence about their perceived ability to make right product selections. In turn, this increases their willingness to try new products, as well as purchase products that are more niche and experiential, which inherently have higher return rates. This contradicts the common belief that multichannel consumers are less likely to return products due to increased information availability about product fit or simply due to greater convenience. For example, Petersen and Kumar (2009) found that consumers who purchased familiar product categories from new channels returned fewer products. Our findings help reconcile the existing literature by showing that consumers tend to return more products when using additional channels because they are buying different products that are more niche and experiential.

Based on the empirical insights, we develop a consumer choice model to predict the choice of channel used to purchase a product and the subsequent return rates. We leverage the prediction model to inform the focal retailer on the choice of channel to distribute niche and experience products. Based on a cross-validation procedure, our model achieves an average of 93% accuracy and Area under the ROC Curve (AUC) score of 0.91 in predicting matches (i.e., the predicted channel by our choice model *matches* the observed channel in the holdout sample). Overall, we find that average return rates are *lower* when the predicted channel from our choice model matches that of the observed channel across the three sample categories (overall, single-channel, and multichannel), between niche and popular products, as well as between experience and search products.

Furthermore, through a series of back-of-the-envelope calculations, we show that although multichannel consumers exhibit a higher return likelihood than single-channel consumers across all the three channels (i.e., online, offline showroom, and catalog), the former group of consumers, on average, generate larger amounts of total revenue in the online and catalog channels than single-channel consumers. While multichannel consumers also generate larger basket values than their single-channel counterparts in the online and catalog channels, their basket values in the showroom channel are smaller. This suggests that multichannel consumers are purchasing either lower value items or fewer units per basket transaction in the showroom channel relative to single-channel consumers in the same channel.

The existing research indicates that retailers generally view product returns as negative. However, high return rates might not always be harmful for retailers. It is important to consider the overall outcome in its entirety. Our analysis in Section 7.3 shows that even though multichannel customers have higher return rates, they also generate more revenue for the retailer. This finding extends previous studies (e.g., Chintala et al. (2023)) which emphasize that channel distinctions play a significant role in the types of product purchased by consumers. For example, comparing grocery shopping data from physical stores and Instacart, Chintala et al. (2023) find that online purchases included fewer product varieties, 13% less fresh vegetables, and approximately 6% fewer impulse buys than offline purchases. Our contribution to this discourse reveals that consumers of different types (multichannel or single-channel) also have distinct risk tendencies and preferences in their product choices. In turn, they also exhibit different return behaviors.

We discuss several practical implications of our findings. The conventional wisdom generally suggests that retailers should feature popular products in physical stores while reserving more niche (or long-tail) items for non-physical channels (Brynjolfsson et al. 2011). This is because non-physical channels typically have more flexibility in terms of inventory storage due to less constraints on physical spaces (Rabinovich et al. 2011). However, our study conducted in a physical store with zero inventory context, shows that consumers actually prefer to purchase niche and experience products in the physical stores rather than non-physical channels (see Table E.1 in Online Appendix E). Additionally, the return rate of products purchased in the showroom is generally lower compared to the other two channels. As a result, retailers operating a network of physical showroom stores in a multichannel or omnichannel capacity should approach product assortment, store layout, and customer targeting differently from traditional retailers who manage brick-and-mortar stores that carry inventory. Specifically, these retailers can focus on featuring a greater variety of niche and experiential products in their stores, while also carefully curating product exhibits to attract customers to visit the stores. By doing so, these retailers can actively reduce the rate of product returns and leverage store associates to communicate product information and help consumers in their purchase decision making process. Moreover, the store associates could strategically cross-sell and upsell products to potentially further increase sales revenue.

Given that multichannel consumers generate more revenue for the retailer even after accounting for the higher return rates compared to single-channel consumers, retailers could consider strategies (e.g., issuing coupons or discount vouchers) to encourage single-channel consumers to explore new channels for making purchases. Additionally, when previously online- or catalog-only consumers become showroom users, retailers can incentivize these consumers to visit the showroom stores to place orders in the store, which can help reduce multichannel consumers' return rates. From a theoretical perspective, the behavioral insights from our study can help inform modeling extensions for analytical and optimization models such as those used in assortment planning, distribution network design and store layout, and customer segmentation and lifetime value analysis.

A limitation of our data is that we do not have access to search data (e.g., clickstream and in-store visits without a purchase). We only observe transaction data. As such, we do not know whether a consumer searches for a product online and then makes a purchase of the product in the showroom store. In fact, such data are currently rare. Since the showroom experience is more effective in improving the accuracy of product information compared to the other two channels, any hidden cross-channel path for product searches would only result in more conservative results.

Our study focuses on two product attributes, namely–niche vs. popular products and search vs. experience products. Future research can expand on the analysis to examine attributes prevalent in other contexts such as perishability in grocery retailing and brand reputation in luxury fashion that might influence return behavior. Additional research can also include a longitudinal analysis to examine how consumers' channel usage and return behavior change over time. This provides insights into the dynamics of multichannel behavior (Ansari et al. 2008) and the long-term impact on product returns. There is also an opportunity to explore heterogenous effects by investigating the heterogheneity of multichannel customer behavior and product returns arcoss different customer segments, such as age, gender, and shopping preferences. Understanding how these factors influence channel choice and return behavior can help tailor strategies to specific customer segments.

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E-Companion: Online Appendix

A. Consumer Purchasing Behavior and Niche/Experience Product Analysis

A.1. Product Nicheness

Our objective in this section is to examine whether multichannel consumers are more likely to purchase niche products than single-channel consumers (P1) and whether more niche products have a higher likelihood of return post-purchase (P2). To do so, we implement two analyses. In the first, we operationalize a continuous measure for product nicheness (*NICHENESS*) using our transaction data. We compute the channel-level total sales for each SKU by multiplying the quantity sold with the units sold (quantity × units sold) in channel. Then, we rank the SKUs based on their sales volume contribution in each channel. The higher the absolute value (or the lower the rank), the more niche the product is. Given there are a total of 689 SKUs during the focal period, we rank the SKUs from 1 to 689. Then, we take the natural log of *NICHENESS* and regress it on the same set of independent variables as Model 2 so that our model is specified as

$$\begin{aligned}\ln NICHENESS_{ik} = \beta_0 + \psi_j + \gamma_k CHANNEL_{ijt} + \boldsymbol{CONTROLS_{ij}} \cdot \beta_1 + \\ \sum_n PRODUCTCAT_n \cdot \theta_{n,i} + \sum_t WEEK_t \cdot \omega_t + \varepsilon_{ik}. \quad \text{(A.1)}\end{aligned}$$

We implement the analysis at the subsample level, that is, single-channel and multichannel consumer subsamples. We observe differences in the magnitudes of the channel coefficients to infer differences in single-channel versus multichannel consumers' tendencies to purchase niche items for confirming P1.

Next, we implement the second analysis, also at the subsample level, by employing Model 2 and including the term ln*NICHENESS* along with its interaction terms with channel (i.e., ln*NICHENESS*× *ONLINE* and ln*NICHENESS*× *CATALOG*) to examine whether niche products have a higher return likelihood and whether the effect varies with sales channel. Any positive and statistically significant coefficient associated with these terms will provide evidence of a higher return likelihood to confirm P2. These results are presented in Tables A.1a and A.1b.

Because the estimates in Table A.1a do not allow for a statistical evaluation to determine whether the values of β_0, γ_o, and γ_c for single-channel consumers differ from those of the multichannel consumers, we employ a bootstrapping procedure to generate the standard errors and the 95 percent confidence intervals (Freedman and Peters 1984). According to Mooney and Duval (1993), 50 to 200 replications are needed for the estimates of standard errors and for the normal-approximation of the confidence intervals. We chose 50 replications for the procedure. Armed with these standard errors, one for each of the three coefficients (β_0, γ_o, and γ_c), we interpret the results in Table A.1a.

The results indeed provide evidence to suggest that multichannel consumers tend to purchase more niche products across all three channels. In the showroom stores, multichannel consumers, on average, purchased products that are ranked 167 out of 689 ($\beta_0 = exp(5.118)$, $SE = 1.20$, $CI = [164.65, 169.35]$) relative to 151.56 ($\beta_0 = exp(5.021)$, $SE = 2.11$, $CI = [147.42, 155.69]$) by the single-channel consumers. Moreover, multichannel consumers in the online channel, on average, purchased products that are ranked 29.70 ($\gamma_o = exp(5.118 - 1.727)$, $SE = 0.66$, $CI = [28.40, 30.99]$) relative to 26.90 ($\gamma_o = exp(5.021 - 1.729)$, $SE = 0.76$, $CI =$

[25.41, 28.39]) by the single-channel consumers. Last, in the catalog channel, multichannel consumers, on average, purchased products that are ranked 486.38 ($\gamma_c = exp(5.118 + 1.069)$, $SE = 2.38$, $CI = [484.09, 491.04]$) relative to 466.37 ($\gamma_c = exp(5.021 + 1.124)$, $SE = 3.39$, $CI = [459.72, 473.01]$) by the single-channel consumers. These results support H2. The results in Table A.1b further suggest that more niche products have a higher odds of being returned (0.289, $p < 0.001$) although the effects do not appear to vary with the online (–0.052, $p = 0.574$) or the catalog (–0.080, $p = 0.888$) channel. Overall, we find support for P2.

Table A.1: Product Nicheness as a Mechanism

Variable	(1) Model A.1 for single-channel consumers	(2) Model A.1 for multichannel consumers
ONLINE	–1.729*** (0.008)	–1.727*** (0.030)
CATALOG	1.124*** (0.003)	1.069*** (0.004)
Control variables		
ln*VOLUME*	–0.297*** (0.001)	–0.249*** (0.003)
FULFILMODE	0.001 (0.001)	–0.008 (0.011)
ln*DISTWC*	–0.001* (0.000)	–0.009** (0.003)
ln*DISTSC*	0.000 (0.000)	0.001 (0.003)
ln*FREQUENCY*	0.002*** (0.001)	–0.007* (0.003)
ln*PRICE*	0.002*** (0.001)	0.002 (0.004)
Constant	5.021*** (0.005)	5.118*** (0.028)
Product Category Effects	Yes	Yes
Week Effects	Yes	Yes
Consumer Effects	Yes	Yes
No. of Observations	272,738	21,610
Adj. R^2	0.911	0.888

Notes. Cluster robust standard errors are reported in parentheses.
* p < 0.05, ** p < 0.01, *** p < 0.001.

(a) Propensity to Purchase Niche Products

Variable	(1) Model 2
ONLINE	1.501*** (0.426)
CATALOG	1.566 (3.624)
ln*NICHENESS*	0.289*** (0.062)
ONLINE×ln*NICHENESS*	–0.052 (0.093)
CATLOG×ln*NICHENESS*	–0.080 (0.570)
Control variables	
FULFILMODE	0.356*** (0.067)
ln*DISTWC*	–0.073* (0.035)
ln*DISTSC*	–0.152*** (0.030)
ln*FREQUENCY*	0.483*** (0.048)
ln*PRICE*	0.060 (0.037)
Constant	–8.231*** (0.382)
Product Category Effects	Yes
Week Effects	Yes
Consumer Effects	Yes
No. of Observations	294.348
Log Likelihood	–34,399.55

Notes. Cluster robust standard errors are reported in parentheses.
† ln*VOLUME* not included due to collinearity with ln*NICHENESS*.
* p < 0.05, ** p < 0.01, *** p < 0.001.

(b) Nicheness and Return Likelihood

A.2. Product Experience

We adopt a similar two-part procedure as in Section 8 to examine whether multichannel consumers are more likely to purchase experience products than single-channel consumers (H4) and whether more experience products have a higher likelihood of return (H5). We use the rater approach of Hong and Pavlou (2014) to operationalize the experience variable (*EXPERIENCE*). To do this, we employ three independent assistants who rate each product category based on three criteria for experiential goods. These ratings are given on a scale ranging from 1 (representing pure search goods) to 7 (indicating pure experiential goods).[1] To calculate an overall rating for each product category, we take the average of the ratings given by the three raters across

[1] To each rater, we supply both the following texts and the three criteria of experiential goods: "For a product, an experience attribute cannot be ascertained before purchase, while a search attribute can be ascertained before purchase. The more experience attribute a product has, the harder it is for you to evaluate it before purchase. Based on your understanding, please answer the following questions: (1) It is important for me to see/touch/hear (whichever applies) this product to evaluate its attributes (1-7); (2) I can adequately evaluate this product using only information provided by the retailer or manufacturer about this product's attributes and features (1-7); and (3) I can evaluate the quality of this product simply by reading information about the product (1-7)" (Hong and Pavlou 2014).

the three dimensions. Our dependent variable is the natural log of $EXPERIENCE$ and we regress it on the same set of independent variables as Model 2 so that our model is specified as

$$\ln EXPERIENCE_i = \beta_0 + \psi_j + \gamma_k CHANNEL_{ijt} + \boldsymbol{CONTROLS_{ij}} \cdot \beta_1 + \sum_n PRODUCTCAT_n \cdot \theta_{n,i} + \sum_t WEEK_t \cdot \omega_t + \varepsilon_i. \tag{A.2}$$

The results in Table A.2a provide additional evidence to suggest that multichannel consumers tend to also purchase more experience products across all three channels. In the showroom stores, multichannel consumers, on average, purchased products that are rated 3.60 out of 7.0 ($\beta_0 = exp(1.280)$, $SE = 0.045$, $CI = [3.51, 3.68]$) relative to products that are rated 3.36 ($\beta_0 = exp(1.212)$, $SE = 0.059$, $CI = [3.24, 3.47]$) purchased by the single-channel consumers. In addition, multichannel consumers in the online channel, on average, purchased products that are rated 3.64 ($\gamma_o = exp(1.280 + 0.012)$, $SE = 0.046$, $CI = [3.55, 3.73]$), higher than the 3.34 rating ($\gamma_o = exp(1.212 - 0.005)$, $SE = 0.061$, $CI = [3.22, 3.50]$) by the single-channel consumers. Last, in the catalog channel, multichannel consumers purchased products that are, on average, rated 3.57 ($\gamma_c = exp(1.280 - 0.007)$, $SE = 0.048$, $CI = [3.47, 3.66]$), which is also higher than the 3.32 rating ($\gamma_c = exp(1.212 - 0.012)$, $SE = 0.062$, $CI = [3.20, 3.44]$) by the single-channel consumers. Therefore, these findings confirm P3. The results in Table A.2b further suggest that more experience products have a higher odds of being returned (1.014, $p < 0.001$) although the effects do not seem to vary with either the online (–0.001, $p = 0.992$) or the catalog (0.113, $p = 0.185$) channel. Overall, we also find support for P4.

Table A.2: Product Experience Level as a Mechanism

Variable	(1) Model A.2 for single-channel consumers	(2) Model A.2 for multichannel consumers
$ONLINE$	–0.005* (0.002)	0.012* (0.006)
$CATALOG$	–0.012*** (0.001)	–0.007** (0.003)
Control variables		
$\ln VOLUME$	–0.004*** (0.000)	–0.010*** (0.002)
$FULFILMODE$	0.016*** (0.001)	0.008 (0.005)
$\ln DISTWC$	0.002*** (0.001)	0.006** (0.002)
$\ln DISTSC$	–0.001* (0.000)	–0.005** (0.002)
$\ln FREQUENCY$	0.019*** (0.001)	0.014*** (0.002)
$\ln PRICE$	–0.032*** (0.001)	–0.040*** (0.003)
Constant	1.212*** (0.005)	1.280*** (0.020)
Product Category Effects	Yes	Yes
Week Effects	Yes	Yes
Consumer Effects	Yes	Yes
No. of Observations	272,738	21,610
Adj. R^2	0.760	0.767

Notes. Cluster robust standard errors are reported in parentheses.
* p < 0.05, ** p < 0.01, *** p < 0.001.

(a) Propensity to Purchase Experience Products

Variable	Model 2
$ONLINE$	0.825*** (0.204)
$CATALOG$	1.229 *** (0.127)
$\ln EXPERIENCE$	1.014*** (0.288)
$ONLINE \times \ln EXPERIENCE$	–0.001 (0.138)
$CATLOG \times \ln EXPERIENCE$	0.113 (0.085)
Control variables	
$\ln VOLUME$	–0.101*** (0.018)
$FULFILMODE$	0.363*** (0.067)
$\ln DISTWC$	–0.073* (0.035)
$\ln DISTSC$	–0.151*** (0.030)
$\ln FREQUENCY$	0.483*** (0.048)
$\ln PRICE$	0.052 (0.036)
Constant	–8.168*** (0.450)
Product Category Effects	Yes
Week Effects	Yes
Consumer Effects	Yes
No. of Observations	294,348
Log Likelihood	–34,383.98

Notes. Cluster robust standard errors are reported in parentheses.
* p < 0.05, ** p < 0.01, *** p < 0.001.

(b) Product Experience and Return Likelihood

B. Heckman Selection Model and Control Function Approach

To address the potential channel-selection bias, we adopt a Heckman selection method (Heckman 1976, 1979). We follow Lee's generalized approach (Lee 1983) to obtain the channel-specific correction term ratio (λ) from a first-stage multinomial Logit model of channel selection. The model is specified as $Pr(CHANNEL_{ij} = k) = exp(\mathbf{X}_{ijk}\Omega)/\sum_{m=1}^{K} exp(\mathbf{X}_{ijm}\Omega)$, where $k = o$, s and c, and $\mathbf{X}_{ij}$ and Ω denote the vector of variables in the selection model and their corresponding coefficients, respectively. We include variables expounded in the extant literature that are likely to influence a consumer's channel choice. These variables include: average product price (in EUR) for SKU i placed by consumer j (Forman et al. 2009), an indicator of whether or not consumer j is a high spender (his/her total expenditures of all transactions greater than sample median, EUR 1,003) (Fox et al. 2004); distance between consumer j and the nearest showroom store (Gallino et al. 2017); full set of demographic controls as used in Section 7.2 to include AGE, $EDUCATION$, $HOUSEHOLDSIZE$, and $HOMEOWNERSHIP$ (Bhatnagar and Ratchford 2004, Fox et al. 2004); as well as product category and week factors. Let $F()$ be the logistic distribution function, $F(\mathbf{X}_{ij}\Omega)$ the predicted probabilities of each channel given $\mathbf{X}_{ij}\Omega$, and the transformation $J = \Phi^{-1}F$. We then compute the correction term ratio via:

$$\hat{\lambda_{ij}} = \lambda(\mathbf{X}_{ij}\hat{\Omega}) = \frac{\phi(J(\mathbf{X}_{ij}\hat{\Omega}))}{F(\mathbf{X}_{ij}\hat{\Omega})},$$

where $\phi(.)$ is the probability density function of a standard normal. In the second stage, we include the computed ratio in each of the regressions as an additional control variable of consumers' channel selection decision. The computed ratio, $\hat{\lambda}$, is a selection parameter and its coefficient accounts for potential selection bias.

Next, we introduce an instrument ($MULTICHOTHER$) for $MULTICH$ that is constructed based on the proportion of multichannel consumers (excluding the focal consumer) in the same ZIP code as the focal consumer. For the instrument to be valid, it needs to satisfy both the relevance criteria and the exclusion restriction condition. We motivate the relevance of this instrument based on the concept of homophily or social influence (Ma et al. 2015). The basic idea is that consumers who are close together (e.g., in the same neighborhood, social network, or ZIP code) are more likely to behave similarly or exhibit similar purchasing behavior. The F-Statistics in Table B.1 is 134.22, which is larger than 10 (Wooldridge 2015), indicating that the instrument is relevant.

The instrument also satisfies the exclusion restriction condition as the share of multichannel consumers in the ZIP code does not directly influence the tendency of the focal consumer to return a product. We then use the instrument in the control function approach (Wooldridge 2015) which estimates a residual term and include it in each of the model in Tables 3, 4, and 5. Armed with both the λ from the Heckman selection process and the residual term from the control function, we reestimate the regressions and provide the results in Tables B.2, B.3, and B.4, respectively. The results are all qualitatively consistent with the main results.

Table B.1: First-Stage Control Function Estimates

Variable	(1) First-Stage Control Function *MULTICH*
ONLINE	0.837*** (0.211)
CATALOG	0.639*** (0.162)
MULTICHOTHER	0.788*** (0.101)
Control variables	
ln*VOLUME*	0.219*** (0.010)
FULFILMODE	0.118*** (0.005)
ln*DISTWC*	0.066* (0.030)
ln*DISTSC*	0.080* (0.040)
ln*FREQUENCY*	0.330*** (0.009)
ln*PRICE*	0.190*** (0.050)
SKU Effects	Yes
Week Effects	Yes
Consumer Effects	Yes
No. of Observations	294,348
Adj. R^2	0.536

Notes. Cluster robust standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.2: Return Behavior with SKU Control, Heckman Selection Correction, and Control Function

Variable	(1) Model 3	Model 3	(3) Model 3†
ONLINE	0.860*** (0.169)	0.811*** (0.201)	0.515*** (0.087)
CATALOG	1.357*** (0.115)	1.271*** (0.172)	0.870*** (0.054)
MULTICH		–0.604*** (0.098)	0.068 (0.060)
Control variables			
ln*VOLUME*	–0.079*** (0.016)	–0.066*** (0.019)	0.064 (0.056)
FULFILMODE	0.392** (0.123)	0.427*** (0.009)	0.260*** (0.075)
ln*DISTWC*	–0.072 (0.090)	–0.076 (0.088)	–0.056 (0.047)
ln*DISTSC*	–0.149* (0.070)	–0.161* (0.080)	–0.087* (0.040)
ln*FREQUENCY*	0.415*** (0.126)	0.402*** (0.116)	0.390*** (0.040)
ln*PRICE*	0.071** (0.022)	0.085*** (0.025)	
$\hat{\lambda}$	0.801*** (0.212)	0.787*** (0.222)	0.876*** (0.207)
Residual		0.888 (0.671)	0.890 (0.700)
SKU Effects	No	No	Yes
Week Effects	No	No	Yes
Consumer Effects	Yes	Yes	Yes
No. of Observations	294,348	294,348	294,348
Log Likelihood	–34,523.25	–34,482.91	–34,216.87

Notes. Cluster robust standard errors are reported in parentheses.
† The estimation function is not concave when both ln*PRICE* and SKU fixed effects are included in the model. Therefore, we excluded ln*PRICE*.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.3: Return Behavior with Heckman Selection Correction and Control Function

Variable	(1) Model 2 for single-channel consumers	(2) Model 2 for multichannel consumers	(3) Model 2 for full sample
ONLINE	0.959*** (0.232)	0.519* (0.238)	0.813*** (0.170)
CATALOG	1.406*** (0.179)	1.041**** (0.137)	1.310*** (0.109)
MULTICH			0.601*** (0.105)
Control variables			
ln*VOLUME*	–0.092*** (0.020)	–0.094 (0.058)	–0.090*** (0.016)
FULFILMODE	0.295 (0.154)	0.789*** (0.183)	0.356*** (0.120)
ln*DISTWC*	–0.079 (0.103)	0.149 (0.115)	–0.062 (0.071)
ln*DISTSC*	–0.147 (0.098)	–0.255** (0.083)	–0.166** (0.064)
ln*FREQUENCY*	0.249 (0.214)	–0.098 (0.148)	0.255* (0.128)
ln*PRICE*	–0.156 (0.126)	0.761* (0.333)	1.096** (0.410)
$\hat{\lambda}$	1.129 (0.599)	0.761* (0.333)	1.096** (0.410)
Residual			0.813 (0.755)
Constant	–8.428*** (0.649)	–4.933*** (0.751)	–7.712*** (0.434)
Product Category Effects	Yes	Yes	Yes
Week Effects	Yes	Yes	Yes
Consumer Effects	Yes	Yes	Yes
No. of Observations	272,738	21,610	294,348
Log Likelihood	–30,254.25	–3,652.44	–34,345.03

Notes. Cluster robust standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: Parallel Mediation Analysis with Heckman Selection Correction and Control Function

Variable	Direct effects [CI]	Total indirect effect [CI]	Mediation paths/subpaths with effect sizes	Indirect effects	95% CIs
MULTICH	0.065 [–0.087, 0.217]	1.808 [1.049, 2.566]	$MULTICH \xrightarrow{2.683} NICHE \xrightarrow{0.286} RETURN$	0.767	[0.529, 1.006]
			$MULTICH \xrightarrow{0.978} EXPER \xrightarrow{1.065} RETURN$	1.041	[0.517, 1.565]

Notes. CI denotes 95% percentile-based bootstrap confidence interval, $MULTICH$, $NICHE$, $EXPER$, and $RETURN$ denote multichannel consumers, niche products, experience products, and return indicator, respectively. Covariates: $CHANNEL$, ln$VOLUME$, $FULFILMODE$, ln$DISTWC$, ln$DISTSC$, ln$FREQUENCY$, ln$PRICE$, $PRODUCTCAT$, $WEEK$, and λ and residual terms from Heckman selection and control function, respectively.

C. Matching Analysis

To account for consumers' higher propensity to gravitate toward using multiple channels in their purchasing due to more intense consumption trajectory, we adopt the risk-set matching procedure in Bell et al. (2020) to implement a matching procedure that compare the evolution of pairs of multi-channel (treated) and single-channel (control) consumers that share similar consumption trajectories prior to the former's first use of a secondary channel. This approach provides better support for a causal interpretation of the return effect based on exposure to the multiple channels.

The procedure creates pairs of "identical" consumers based on similar observable characteristics. To ensure proper comparison, these pairs are formed in a way that treatment and control consumers share similarity before treatment (i.e., first usage of a second channel), considering that treatment consumers can adopt a second channel at different time points. In risk-set matching, a newly treated consumer at time t is matched with one or more control consumers not yet treated at the same time t. We match consumers who receive treatment at time t (i.e., first usage of a second channel at time t) with consumers who had the same treatment probability at time t, meaning they had the same hazard rate, but opted not to adopt a second channel. In this way, we prevent any potential bias in our comparison of the outcomes of interest that could arise if a control consumer were to use a secondary channel at a later time.

At time t, treatment occurs when consumer j adopts a second channel for the first time. We match consumer j at time t with another consumer l from the control group, who never used a second channel (i.e., single-channel consumers who stick to using only a single channel) during the analysis period. We select the control consumer that best matches the treated consumer at the time. We consider consumer characteristics and variables that summarize the purchasing trajectory of a consumer. These variables can change over time and are used in the matching process. We use several variables that have shown to be influential in consumers' choice of sales channel for matching consumer j before time t. Consistent with Bell et al. (2020), these variables include the total number of transactions, the time since last purchase, the total dollar sales, the total number of unique subcategories purchased, and the distance from consumer j's ZIP code to the nearest showroom store at time t. Following the approach by Rosenbaum et al. (2010), we do not restrict a control consumer to be matched with only one treatment consumer. We use a nearest neighbor matching method with Mahalanobis distance based on the five covariates mentioned earlier. The matching is done on a 1:1 basis between treated and control consumers. We also considered several other matching alternatives; our results remain consistent across different combinations of matched units (i.e., number of matches per treated unit) and distance metrics.

For the analysis, we use only the pool of consumers whom we observe their actual channel adoption sequence, in the case of adopting an additional channel, if any. We retain 3,794 consumers: from 1,897 treatment consumers who used a second channel for their purchases and the corresponding best match for each treatment consumer from the pool of control consumers who maintained as single-channel consumers. The results in Table C.1 demonstrate that the matching procedure was effective in creating treatment and control groups that are virtually identical to each other across the set of matching covariates. With the matched sample, we compare the return rates for the treated versus control consumers using the following specification:

$$RETURNRATE_{m,j} = \alpha_0 + \beta_1 Treatment_j + Pair_m + \varepsilon_i, \quad \text{(C.1)}$$

where m denotes the matched pairs, j indicated whether the consumer is treated or control ($j \in$ $treated, control$), $Treatment_j = 1$ for $j = Treated$ and 0 otherwise, and $Pair_m$ is a fixed effect for each matched pair. The dependent variable of interest is $RETURNRATE$ which is the number of returns divided by the total number of transactions for each consumer. Relative to their matched control counterpart, the results in Table C.2 show that treated consumers generate an average of 2.7% more returns over their subsequent purchase history following their first usage of a second channel ($p < 0.001$). Overall, these results are consistent with the main results in Table 4.

Table C.1: Average Covariate Balance Across Treated and Control Consumers

Variable	Description	(2) Multi-channel Consumers (Treated)	Single-channel Consumers (Control)
Sales	Total sales amount prior to first usage of a secondary channel for treated consumer	1011.78 (1201.52)	1012.22 (1186.01)
SubCat	Number of subcategories purchased	3.13 (2.16)	3.10 (2.32)
MinDist	Minimum distance to a showroom store	23.88 (24.32)	24.76 (24.77)
Sequence	Number of orders transacted with the focal retailer	1.49 (0.69)	1.49 (0.60)
Recency	Time (in days) since last purchase	6.00 (12.19)	5.99 (11.55)

Notes. Standard errors are in parentheses. There are 1,896 observations per group.

Table C.2: Risk-Set Matched Sample Estimation Results

Variable	(1) Model C.1 AvgReturnRate
Treatment	0.027** (0.010)
Pair Effects	Yes
Constant	Yes
No. of Observations	3,792
R^2	0.216

Notes. Robust standard errors are reported in parentheses.
* p < 0.05, ** p < 0.01, *** p < 0.001.

D. Online Experiment on the Effect of Multichannel Usage on Consumers' Confidence and Willingness to Purchase Niche and Experience Product

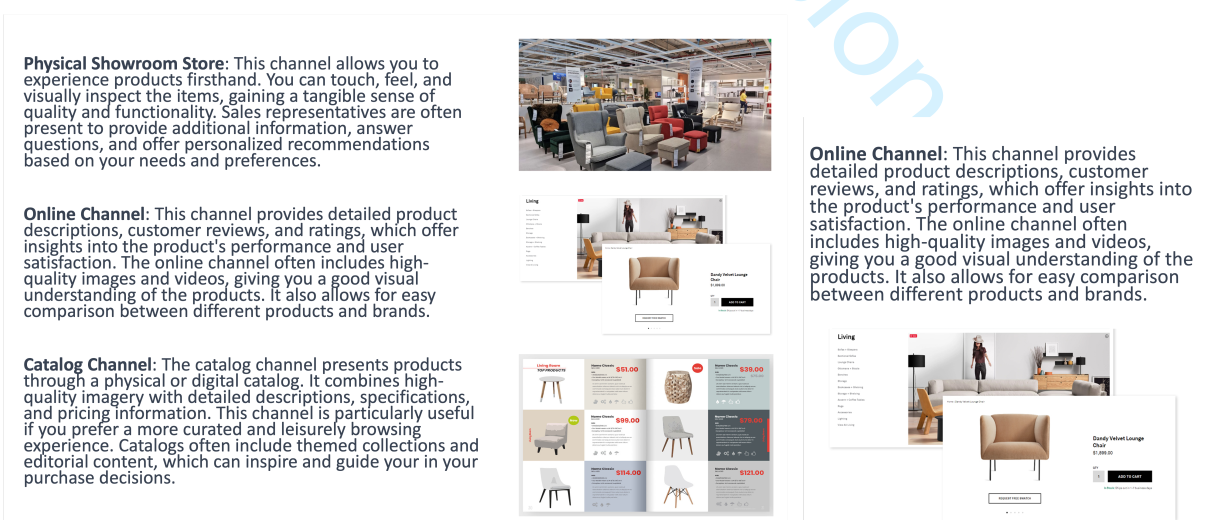
D.1. Participants

We recruited 300 participants from Amazon Mechanical Turk and offered $1.00 for each participation. We chose the sample size of 300 participants to capture 150 observations per condition. 10 participants did not complete all tasks as instructed and was removed from the sample. This results in a final data set of 290 participants. In this sample, the average age is 39.4 years old, and approximately 43.5% of the participants are females. Moreover, 89% of the participants have at least a bachelor's degree.

D.2. Design and Procedure

At the beginning of the experiment, we told the participants to read a hypothetical online shopping scenario carefully and answer the questions. We then randomly assigned the participants into either a multichannel condition or a single-channel condition (see Figure D.1). Both conditions asked the participants to imagine that they were shopping for a lounge chair on the Internet for their new apartment. They are examining a lounge chair that is supplied from a small manufacturer with several unique features including automatic incline, waterproof material, and memory foam. These features are not widely available in the current market. Because the product is produced by a small manufacturer, they are not aware of the brand and reputation of the manufacturer. Both groups of participants were asked to evaluate the same lounge chair. The difference is the type of information they can obtain from a specific sales channel. In the case of multichannel condition, the participants can obtain various types of information available in the physical store, online, and catalog channel. Whereas in the case of single-channel condition, the participants can only obtain information specific to the online channel such as product descriptions and customer ratings.

Figure D.1: Screenshots of the Scenarios



(a) Multichannel Condition (b) Single-Channel Condition

After that, we adapted items in Bearden et al. (2001) for consumer confidence and Goldsmith and Hofacker (1991) for consumer innovativeness and asked the participants to rate: (1) "Given your access to the sales channel(s), to what extent do you feel confident about your ability to make the right purchase selection/decision?" and (2) "Given your access to the sales channel(s), to what extent are you willing to purchase new (or newly released) products?," each on a sliding scale from 0 (Not at all) to 100 (Very much so).

Next, we asked the participants to rate: (3) "To what extent are you willing to purchase the product that has rich touch-and-feel attributes (e.g., need to see/touch to fully evaluate the product) based on information you obtain from the sales channel(s)?" on a sliding scale from 0 (Not at all likely) to 100 (Very likely). This item provides the measure for participants' willingness to purchase experience products. To obtain the measure for participants' willingness to purchase niche products, we asked the participants to rate: (4) "To what extent are you willing to purchase less known (i.e., less popular) product based on information you obtain from the sales channel(s)?" on a sliding scale from 0 (Not at all likely) to 100 (Very likely). We used these inputs to measure consumer purchasing confidence and willingness to purchase niche and experience products, which are the variables reported in Table 6 of the main paper.

Finally, we collected some demographic information including age, gender, education background, and past experience with purchasing a lounge chair as control variables to isolate the effects of interest.

E. Channel Choice Estimation Results

Table E.1: Channel Choice

Variable	Online channel	Catalog channel
MULTICH	0.625*** (0.157)	0.860*** (0.102)
ln*NICHENESS*	–0.012* (0.006)	–0.779*** (0.230)
ln*EXPERIENCE*	–0.440* (0.221)	–1.826*** (0.509)
MULTICH ×ln*NICHENESS*	0.020 (0.020)	0.070*** (0.010)
MULTICH ×ln*EXPERIENCE*	–0.009* (0.004)	–0.085** (0.029)
ln *VOLUME*	–0.461*** (0.031)	–0.728*** (0.031)
FULFILMODE	–0.180 (0.179)	–0.496*** (0.031)
ln*DISTWC*	–0.023 (0.086)	–0.258*** (0.059)
ln*DISTSC*	0.510*** (0.079)	0.693*** (0.054)
ln*FREQUENCY*	–0.693*** (0.102)	–0.531*** (0.063)
ln*PRICE*	–0.909*** (0.032)	–1.316*** (0.034)
AGE	0.015 (0.027)	–0.029 (0.025)
HOUSEHOLDSIZE	–0.322 (0.259)	–0.486* *(0.217)
HOMEOWNERSHIP	–0.085 (0.687)	–0.792 (0.416)
EDUCATION	0.856 (1.064)	2.267*** (0.576)
FULFILMODE×ln*NICHENESS*	–0.047* (0.020)	–0.033 (0.017)
ln*DISTWC*×ln*NICHENESS*	–0.013 (0.010)	0.022* (0.010)
ln*DISTSC*×ln*NICHENESS*	–0.001 (0.008)	–0.015 (0.009)
ln*FREQUENCY*×ln*NICHENESS*	0.002 (0.011)	0.017 (0.009)
AGE×ln*NICHENESS*	–0.008* (0.003)	–0.003 (0.004)
HOUSEHOLDSIZE×ln*NICHENESS*	–0.071* (0.032)	–0.030 (0.036)
HOMEOWNERSHIP×ln*NICHENESS*	0.050 (0.111)	0.077 (0.071)
EDUCATION×ln*NICHENESS*	0.221 (0.163)	0.116 (0.128)
FULFILMODE×ln*EXPERIENCE*	–0.147* (0.068)	–0.104* (0.046)
ln*DISTWC*×ln*EXPERIENCE*	0.048* (0.020)	0.063* (0.025)
ln*DISTSC*×ln*EXPERIENCE*	–0.038 (0.023)	–0.049 (0.026)
FREQUENCY×ln*EXPERIENCE*	–0.075** (0.027)	–0.184*** (0.025)
AGE×ln*EXPERIENCE*	–0.005 (0.010)	–0.024** (0.008)
HOUSEHOLDSIZE×ln*EXPERIENCE*	0.035 (0.091)	0.212** (0.076)
HOMEOWNERSHIP×ln*EXPERIENCE*	0.244 (0.192)	0.078 (0.151)
EDUCATION×ln*EXPERIENCE*	0.709** (0.223)	0.067 (0.207)
Product Category Effects	Yes	
Week Effects	Yes	
Consumer Effects	Yes	
No. of Observations	206,043	
Log Likelihood	–94,140.98	

Notes. Cluster robust standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.