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Demand Effects of the Internet-of-Things Sales Channel: Evidence from Automating the Purchase Process

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Abstract. The internet of things (IoT) is rapidly becoming one of the most popular emerging technologies in business and society. One of the major verticals that has recently begun to effectively use IoT technologies is the retail industry. Given the unprecedented opportunities IoT generates for brands and retailers, it is important to glean timely insights regarding the business value of IoT and understand whether the introduction of an IoT technology as an alternative purchase channel for consumers affects the sales of physical products. In this paper, using empirical data from a multinational online retailer that adopted an IoT technology that largely automates consumers' purchases and a quasi-experimental framework, we study the effect of the introduction of IoT on product sales. Our analyses reveal a statistically and economically significant increase in sales as a result of adopting an IoT technology and demonstrate the business value of the IoT channel for retailers and brands. In addition, we conduct analyses of the IoT phenomenon to also delve into the effect heterogeneity and empirically validate the underlying mechanism by examining the impact of IoT for products in different price ranges, levels of substitutability, and product categories (e.g., search versus experience goods and hedonic versus utilitarian), drawing on mental accounting and automaticity theory. For instance, our analyses reveal that less expensive and more differentiated products as well as experience and utilitarian goods can accrue higher benefits leveraging more effectively novel IoT technologies. We validate the robustness of our findings using an extensive set of robustness checks and falsification tests. This is the first paper to study the impact of an IoT technology on product sales, drawing important theoretical and managerial implications and seeding new future research directions for devices and technologies largely automating the purchase process.

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1. Introduction

The internet of things (IoT) is rapidly becoming one of the most popular emerging technologies in business and society. The IoT refers to uniquely identifiable physical objects embedded with electronics, sensors/actuators, software, and wireless network connectivity that enable these objects to exchange data over the internet with low energy consumption (e.g., IEEE 2014, ITU 2015, Minerva et al. 2015, Venkataramani et al. 2018). It has been projected that by 2020, the world will see 30–50 billion internet-connected objects (Evans 2009, Ericsson 2017), whereas business IoT spending is forecasted to reach almost $3 trillion (Gartner 2017). These remarkable projections position the IoT technology as potentially one of the biggest information technology (IT) evolutions of our time. As a result, it is expected that IoT will have a great impact on the economy by transforming many enterprises into digital businesses and facilitating new business models as well as improving efficiency and generating new forms of revenue (Al-Fuqaha et al. 2015).

One way IoT might generate additional revenue for businesses is by creating opportunities for more direct integration of human actions and the physical world into computer-based systems (Da Xu et al. 2014). Such an interconnection of devices is expected to facilitate automation and reduce human intervention in many business verticals. One of the fastest growing verticals that has recently begun to use IoT to catalyze automation is the retail industry (Gregory 2015, Drinkwater 2016). For instance, the retail industry has begun to use IoT in order to accomplish efficient commercial transactions. In such an IoT-enabled shopping future, internet-connected devices could largely automate the purchase of everyday items on behalf of consumers with reduced human interaction. Whereas some retailers and brands have devised strategies to adopt IoT technologies, others have already begun to leverage IoT in order to minimize consumer interactions and enhance customer experience (Evans 2017). Amazon is an example of a company that uses IoT technologies in retail for product purchases and efficient transactions (Greenfield 2017). Such largely automated consumerism can generate tremendous opportunities for brands and retailers because it makes the purchasing process more frictionless and convenient, integrating human actions and the physical world into computer-based purchase systems.

Despite the promising opportunities of IoT technologies for retailers and brands, currently, there also exist significant barriers to the adoption and deployment of such technologies. In particular, a survey conducted by Gartner cites the lack of clarity about the corresponding business benefits as the top overall challenge to the adoption of IoT technologies; 50% of all respondents ranked it as a top challenge, whereas 70% of those not planning to implement IoT solutions cited it as a major challenge (Brand and Geschickter 2016). Similarly, a survey by eMarketer indicates that 37% of all the respondents cite the difficulty of showing the business value of IoT as the second most significant challenge to the adoption of IoT technologies (eMarketer 2017).

Given these significant barriers hindering the seemingly unprecedented opportunities IoT has to offer brands and retailers, it is important to understand whether the introduction of an IoT technology into the consumers' purchase channel sets affects product sales. This importance is buttressed by the multiple competing arguments regarding the potential effect of IoT. For instance, there may be no effect on product sales from such an adoption if consumers simply continue purchasing the same products with the same frequency as before but potentially from different purchase channels (Hand et al. 2009). Alternatively, the introduction of IoT technology as an alternative purchase channel could decrease product sales because of the choice overload consumers may experience from the increased number of shopping channels (Schwartz 2004). A decline in product sales for products offered via the IoT channel could also result from reduced overpurchasing or stockpiling behavior of consumers. That is, allowing consumers to order products with minimum interaction through IoT technologies might result in a reduction in presently purchased quantities because of lower expected future transaction costs. Another concern of IoT is a decline in the ability to upsell or cross-sell that results from habituation.

Similarly, a reduction in product sales might occur because of reduced shopping enjoyment; consumers might face a less gratifying shopping experience because of their minimized interactions in this new purchase channel (Devaraj et al. 2002). On the contrary, it is also possible that the introduction of IoT technologies in the purchase process may positively impact product sales. An increase in product sales could occur because of the convenience of this purchase channel for consumers or potential changes in the consumers' path to purchase. For instance, making payments less salient and reducing intangible acquisition and replacement costs increase transaction utility and can make products easier to consume and weaken the aversive impact of payments while minimizing any rationing. Similarly, introducing IoT technologies that enable product purchases with minimum human interaction might result in increased automaticity, leading to consumer inertia and reduced variety-seeking behaviors; consumers might not reevaluate their product and brand choices in future orders, leading to increased consumer loyalty toward the corresponding brands and retailers (Chintagunta 1998) as well as increased product demand for the products offered via the IoT technologies. Hence, the significance and directionality of the effect of the IoT channel on product sales remain empirical questions. Apart from unveiling the directionality of the potential effect, it is also important to identify the magnitude of the effect in order to better assess the added business value of such IoT technologies.

Beyond examining whether the introduction of the IoT-enabled channel into the consumers' purchase channel sets affects product sales, it is of paramount importance for managers and retailers to also understand what types of products accrue the highest benefits, if any. The literature has demonstrated that different sales channels can be more beneficial for different types of products. For instance, the introduction of the desktop personal computer (PC) shopping channel to the channel mix has benefited hedonic products more than experience goods (Girard et al. 2003, Kushwaha and Shankar 2013). Hence, we conduct additional analyses and also delve into the heterogeneity of the IoT channel effect for different product taxonomies and characteristics, further enhancing the theoretical and managerial implications of our study while also empirically verifying the underlying mechanism of the observed effect. Delving into the differences in the impact of the IoT channel and conducting in-depth analyses of the IoT effect can provide richer theoretical insights while helping businesses and practitioners make better technology investments and efficiently leverage the IoT as a sales channel.

Using empirical data from an online retailer who adopted an IoT technology that largely automates the consumers' purchases, minimizing human interaction, and utilizing a quasi-experimental design, this paper studies the effect of the introduction of an IoT technology as a purchase channel on product sales and demonstrates the business value of IoT for retailers and brands. We also deepen understanding of the effectiveness of IoT technologies on sales growth by conducting additional analyses to examine important moderating effects of this relationship and validate the underlying mechanism. For instance, we investigate whether the degree of product substitutability, as well as whether a product is more a search or an experience good, moderates the effectiveness of the introduction of the IoT technology on product sales. This is the first paper to study the impact of an IoT technology on product sales, and thus, this paper contributes, among others, to literature that examines how the adoption of information systems artifacts and internet technologies affect product sales, as well as to the emerging literature on IoT technologies.

Our analyses reveal that when a product becomes eligible for purchase also through the IoT channel, product sales experience a statistically and economically significant increase, highlighting the business value of IoT technologies for retailers and brands. The results remain robust across multiple identification strategies and model specifications. The underlying mechanism is also explained and empirically verified based on behavioral and economic theories. Delving into the heterogeneity of the IoT effect, our analyses also reveal that less expensive products can benefit more from the introduction of the IoT channel. Moreover, our findings reveal that experience goods, rather than search goods, benefit more from this introduction. Similarly, utilitarian goods, rather than hedonic goods, benefit more from the introduction of the IoT channel. In addition, more substitutable products benefit less from the IoT channel. The heterogeneity bolsters the overall contribution of the paper because it further empirically verifies the underlying mechanism and enhances the generalizability of the results. Interestingly, our findings also show that the increase in demand for treated products is not simply the result of new customers in the marketplace or a decrease in demand for competitive products or sales of alternative retailers, suggesting that it is mainly because of an increased demand from the existing customer base of the retailer in the marketplace. These findings further verify empirically the underlying mechanism drawing on mental accounting and automaticity theory, as discussed in Sections 3.2 and 5.2. These findings also inform, among others, future literature on sales channels as well as retailer and platform competition.

Beyond the above-mentioned contributions to the literature, our findings also have important managerial implications because we demonstrate the demand effects of the IoT sales channel. Besides, managers can now further understand which products would accrue higher benefits from leveraging more effectively the novel IoT technologies and which would benefit less. These findings, apart from being statistically and economically significant, are also timely and generate interesting insights. Despite the promising opportunities of IoT for retailers and brands, there currently also exist significant barriers to the adoption and deployment of such technologies. We hope that our research paves the way toward further exploring the business value of IoT and contributes to the adoption of devices and technologies largely automating the purchase funnel and enhancing the convenience for consumers.

This paper is organized as follows. Section 2 provides an overview of the relevant streams of literature and highlights the contributions this paper makes to the related work. Then Section 3 describes the data, the IoT devices, and the relevant purchasing process, as well as the differences from other sales channels. Section 4 outlines the empirical methodology and main identification strategy. Section 5 discusses the results of the proposed empirical models and specifications: Section 5.1 describes the main empirical results and the additional identification strategies; Section 5.2 presents further analyses of the main IoT effect and discusses various heterogeneity effects, helping us to empirically verify the identified mechanism; Section 5.3 presents extensive robustness checks, including additional identification strategies and alternative explanations; and Section 5.4 conducts multiple falsification tests. Finally, Section 6 makes conclusions and discusses the implications of our study.

2. Literature Review

The emergence of the internet and the advent of new digital devices have instigated the introduction of additional sales channels offered by retailers over recent decades. A relevant stream of literature has examined the effect of adding certain sales channels, such as a desktop PC (hereafter electronic) or a mobile channel, into an existing channel mix on product sales and other firm performance metrics. The corresponding literature has shown that the introduction of these additional shopping channels can lead to different outcomes depending on their characteristics, ranging from the cannibalization of overall sales to the generation of significant incremental product demand (e.g., Goolsbee 2001, Ansari et al. 2008, Brynjolfsson et al. 2009, Forman et al. 2009, Xia and Zhang 2010).

More specifically, some of the aforementioned studies have documented that the addition of such a sales channel can enhance product sales and generate synergy effects. For instance, Xia and Zhang (2010) find that the adoption of an electronic channel in addition to traditional sales channels yields significant improvements in sales, whereas Deleersnyder et al. (2002) find that when the impact on sales was significant in the information goods industry, it was likely to be positive. Examining an alternative order of channel entries, Avery et al. (2012) study the impact of adding an offline store to the current channel mix and find that in the long run, both catalog and electronic channels benefit from brick-and-mortar store presence. Likewise, Wang and Goldfarb (2017) provide empirical evidence that when an offline store opens, there is a positive impact on sales. Supplementing existing shopping channels with a new electronic channel can, however, also pose threats to firms. For instance, Van Nierop et al. (2011) find a decrease in sales due to the electronic channel, and Forman et al. (2009) find that people substitute away from online purchasing when a store opens locally, whereas Brynjolfsson et al. (2009) find that an increase in local stores decreases demand from the internet and catalog sales channels.

Recently, the proliferation of new digital devices for consumers, such as smartphones and tablets, has led to the introduction of the respective new sales channels (Todri and Adamopoulos 2014). The corresponding literature has started to investigate whether the adoption of such channels affects product sales. For instance, Wang et al. (2015) find that the introduction of a mobile channel increases product sales. Likewise, Liu et al. (2016) find that such an introduction of a mobile channel increases consumers' demand for digital services. Finally, delving into the introduction of a tablet sales channel, Xu et al. (2016) find that the introduction of tablets enhances the overall growth of a retailer's e-commerce sales.

In addition, the extant literature on marketing and information systems has also examined the different dimensions and characteristics of sales channels (e.g., Alba et al. 1997, Verhoef et al. 2007). These dimensions and characteristics include the price level, purchase effort, purchase convenience, service quality, and after-sales service of sales channels (Alba et al. 1997, Verhoef et al. 2007). As we discuss in the next section, the IoT sales channel lowers the purchase effort and increases the purchase convenience because it alters the efficiency, ease, and speed at which products can be purchased, reducing difficulty and time costs for consumers. The importance of these characteristics of the IoT sales channel is also demonstrated by the classical 4Cs marketing model that includes the dimensions of cost and convenience (Lauterborn 1990, Verhoef et al. 2007). Apart from the customer transaction costs and convenience (Verhoef et al. 2007), another sales channel dimension of relevance (Lauterborn 1990) is altering the consideration set information availability (Alba et al. 1997, Verhoef et al. 2007) because the IoT sales channel shortens the purchase funnel and more directly integrates human actions and the physical world into computer-based systems, as further discussed in the next section.

To the best of our knowledge, this is the first paper to study the impact of the IoT-enabled sales channel on product sales; thus, this paper contributes to the streams of literature that examine how shopping channels based on information systems artifacts and internet technologies affect product sales as well as the emerging literature on IoT technologies. Conducting additional analyses of the IoT effect and examining important moderating effects of the relationship of IoT technologies with sales growth further validates the identified mechanism and enhances the contribution of this paper. Besides, such analyses strengthen our understanding around which products would accrue the highest benefits, leveraging more effectively the novel IoT technologies yielding incremental product demand. These findings highlight the business value of the IoT technology for retailers and brands while offering timely implications for future research.

3. Empirical Background and Data Description

In Section 3.1, we describe the empirical setting of this study and the product purchase process through the novel IoT sales channel. We also describe the distinguishing IoT characteristics embodied in the corresponding IoT devices, and we further elaborate on the differences from other sales channels. Then Section 3.2 describes the data set used to study the effect of the IoT channel on product sales.

3.1. IoT Devices and Product Purchase Process

The newly adopted IoT channel enables customers and retailers to transform the traditional product purchase process, reducing human interaction during the shopping process. Thanks to the introduction of the IoT channel, orders for product purchases can be placed on the online retailer marketplace by IoT devices. The IoT devices—owned by the consumers and designed by the marketplace—constitute the relevant "things" from a user and application perspective in the corresponding IoT system. These IoT devices are connected to the internet, the second component in the IoT system, through a required Wi-Fi connection that gives the devices the necessary online access to connect to the retailer marketplace and place product orders using their programmable embedded intelligence and the corresponding cloud IoT infrastructure of the online marketplace.

In detail, apart from a Wi-Fi module designed specifically for IoT devices that provides to the things access to the internet, these IoT devices also embed several other modules that are essential for the IoT

(Minerva et al. 2015) and the purchase process in our empirical setting. More specifically, as illustrated in Figure A2 of the online appendix, the IoT devices also include as fallback mechanisms low-energy Bluetooth and ultrasound microphone and sensor modules (in addition to a few other chips) connected on the circuit board and powered by an embedded battery in order to ensure the connectivity of the IoT device and successful completion of the product orders and other functions. Thanks to the IoT-centric design of the low-energy connectivity modules and fallback mechanisms embedded in the devices, the connections to the online marketplace are ubiquitous because they are available when and where needed according to our empirical setting. In particular, the manufacturing of the IoT devices is centered on this principle (i.e., energy usage, connectivity modules, etc.), embedding modules that allow these devices to be functional for about 15–20 years without any maintenance. In addition to the aforementioned connectivity modules, the IoT devices also embed a sensor/actuator that can be triggered by consumers, and thus, the devices possess a sensing/actuating capability that is essential for IoT systems (Minerva et al. 2015). When the sensor/actuator is triggered, the IoT device uses the aforementioned ubiquitous connectivity as well as the embedded intelligence and knowledge functions as tools in order to make requests/calls directly to the marketplace application programming interfaces (APIs)[1] to place an order based on standard and interoperable communication protocols (Minerva et al. 2015); provide the consumer's username and password to the marketplace, the unique identifier of the IoT device, and the corresponding product identifier; accept the purchase terms on behalf of the consumer; offer security intelligence; and so on. Such orders placed by the IoT devices for consumers are then fulfilled by the marketplace retailer without the need for the consumer to take any further actions, such as inspecting the purchase terms and conditions, providing credit card information and delivery address, explicitly confirming the purchase, and so on. Similar to other sales channels, consumers receive a notification email confirming the purchase,[2] and the products are then shipped to the corresponding delivery address of the consumer. Overall, all the terms and conditions and policies regarding consumer purchases are the same across all shopping channels of the retailer marketplace, including shipping times and product replacements and returns. Finally, after an order has been placed through any one of the purchase channels, consumers can track their product orders through a mobile app and/or the corresponding website of the platform. Figure A1 in the online appendix offers a schematic representation of the product purchase process via the IoT channel described earlier, and Figure A2 illustrates the main components of an IoT device chip.

Beyond the aforementioned components that were described as part of the purchasing process in the IoT channel (e.g., connectivity, ubiquity, actuation, etc.), the IoT devices, thanks to their design, also encompass several other distinguishing characteristics of the IoT (Minerva et al. 2015). For instance, using the embedded modules, the devices are also able to self-configure themselves and their resources. The IoT devices also self-manage the wireless connections, reserve energy whenever it is appropriate, and run diagnostics, too. In addition, the IoT devices are also programmed by consumers during the initial setup, allowing them to order different products for different consumers without the need for physical changes in the IoT device.[3] The devices can also be reprogrammed at a later stage. Briefly, after the initial setup of the IoT devices by consumers, when the sensor/actuator of the devices is triggered, the knowledge functions of the device and the relevant infrastructure of the marketplace are automatically used to submit the product order to the online marketplace, and the order is then fulfilled by the retailer with the delivery of the product to the consumer, as illustrated in Figure A1 and described in detail earlier.

3.2. Underlying Mechanism

As depicted in the above-described process, the IoT channel exhibits several differences from existing sales channels because it reduces human interaction in the purchasing process and more directly integrates human actions and the physical world into the computer-based systems. In particular, the IoT channel greatly enhances the convenience and reduces the effort of making a purchase because it alters the efficiency, ease, and speed at which products can be purchased, reducing the time and the cognitive and physical effort involved in the process. Hence, consumers who use the IoT sales channel face lower intangible (nonmonetary) transaction costs. This reduction in intangible acquisition and/or replacement costs—due to increased purchase convenience and reduced effort—is a main mechanism that could increase the quantity consumers use (in total and per consumption incidence) and minimize rationing, as supported by both economic and mental accounting frameworks (Schary 1971, Wansink 1996, Wertenbroch 1998, Chandon and Wansink 2002).

More specifically, economic and mental accounting theory studies demonstrate that consumers alter their consumption of a product to mentally recover its acquisition and replacement costs, including nonmonetary costs related to time utilization, handiness, appropriateness, accessibility, unpleasantness, and so on (Gehrt and Yale 1993, Gourville and Soman 1998, Prelec and Loewenstein 1998, Chandon and Wansink 2002).

Hence, the reduction in such intangible acquisition costs makes IoT-eligible products easier to consume and positively influences the perceived value for consumers, therefore increasing the quantity of these products consumers use (Gupta and Kim 2010). This is also in accord with transaction utility theory (Thaler 1985) and prospect theory (Kahneman and Tversky 2013), illustrating that transaction utility can increase product demand even when acquisition utility remains constant (Thaler 1985), because transaction costs and inconvenience can be seen as economic losses (Thaler 1980), and transaction utility is a direct determinant of total utility (Gupta and Kim 2010). Part of this reduction in intangible costs and increased ease of purchasing is also the decoupling of ordering a product and paying for it (Prelec and Loewenstein 1998, Thaler 1999). That is, the previously described purchase process—including the automated acceptance of all purchase terms and the automated credit-card payment—enables mental accounting advantages of decoupling purchases and payments, making payments less salient, which can enhance the pleasure derived from consumption and increase transaction utility and product sales because thoughts of past and current payments can undermine the pleasures of consumption (Borgida and Howard-Pitney 1983, Prelec and Loewenstein 1998, Soman 2001, Soman and Gourville 2001, Gupta and Kim 2010).

Similarly, reducing such imminent costs increases the quantity consumers use because it avoids lessening consumption when supplies diminish, thanks to the reduction in intangible replacement costs (Folkes et al. 1993); increases consumption desires (Wansink 1996, Chandon and Wansink 2002); and leads to perceptions of lower unit costs (Folkes et al. 1993). These effects can be accentuated for the IoT because the ease, convenience, and efficiency are salient (Reilly 1982, Gehrt and Yale 1993, Chandon and Wansink 2002) as a result of the more direct integration of the physical world and the consumer actions at the time of consumption into computer-based purchase systems. The increased salience of the ease and convenience further accentuates the impact of the IoT sales channel, contributing to the demand increase because it provides seamless access to purchasing operations and hence products (e.g., Reilly 1982, Gehrt and Yale 1993, Chandon and Wansink 2002), creating a perception of a virtually endless supply according to mental accounting theory (Schary 1971, Wansink 1996, Wertenbroch 1998, Chandon and Wansink 2002). Additionally, the literature on mental accounting theory has demonstrated product demand effects for a variety of products (e.g., Folkes et al. 1993, Wansink 1996, Chandon and Wansink 2002). According to the mental accounting theory mechanism, such an increase in product demand resulting from lowering the purchase effort and increasing the purchase convenience would be higher for cheaper products because transaction costs are proportionally higher for low-cost products, and hence, the reduction in total acquisition cost is larger for such products. This is also in accordance with prospect theory and the Weber–Fechner law of psychophysics because consumer perceptions are more attuned to percentage rather than absolute changes and magnitudes, and hence, such effects are accentuated for cheaper products (Stigler 1965, Thaler 1980, 1985). This is also supported by behavioral research showing that both added shopping convenience and higher product stock availability at home increase consumption quantities more for cheaper products (Chandon and Wansink 2002), as well as that consumers regard time as more important than money, particularly for low-cost products (Eggert and Ulaga 2002, Gupta and Kim 2010). The demand increase would also be higher for utilitarian goods because consumers have a higher willingness to pay in time for hedonic products and consider more important the reduction of intangible transaction costs for utilitarian goods (Burke 2002, Okada 2005). Similarly, the demand effect would also be higher for experience goods because consumers consider more important the reduction of intangible transaction costs, such as time, when shopping for experience goods (Burke 2002) and are willing to spend more time when shopping for search goods (Huang et al. 2009). This is also supported by the theories of Nelson (1970, 1974), as well as extant empirical research showing that consumers prioritize website and physical store features that reduce the shopping time for experience goods rather than for search goods (Burke 2002). In addition, the demand increase would be higher for more differentiated products because transaction costs are higher for such products (Dick and Basu 1994). In addition, such a reduction in transaction costs and increase in time efficiency and ease of use would be expected to have a larger impact on existing users than new users (Chiu et al. 2009, Avery et al. 2012) because existing users desire convenience and are looking for more time-efficient ways to purchase (Alba and Hutchinson 1987, Avery et al. 2012). Moreover, in addition to lowering the purchase effort and increasing the purchase convenience, the IoT sales channel enhances the automaticity of the purchase process because purchases can now be conducted in a largely automated way and without much conscious control (Alba and Hutchinson 1987) as a result of the more direct integration of human actions and the physical world into computer-based purchase systems. This enhanced automaticity is the second potential mechanism because it can further increase consumers' switching costs to alternative products by intensifying the mental processing costs of determining and evaluating a consideration set. Hence, by shortening the traditional purchase funnel path, coupled with reducing the consideration set information availability (Alba et al. 1997, Verhoef et al. 2007), the IoT sales channel can increase product demand for IoT-eligible products. Such an increase in product demand as a result of automaticity would be higher for cheaper products as well as experience and differentiated goods, for which consumers exhibit higher loyalty levels and switching costs are relatively higher (Bharadwaj et al. 1993, Dick and Basu 1994).

However, at the same time, the IoT channel can also reduce consumers' potential enjoyment and pleasure derived from the shopping process compared with other traditional channels used by retailers. Hence, if consumers experience such a reduction in shopping pleasure, the transaction utility of consumer purchases might be reduced, affecting, in turn, product demand. In addition, another difference of the IoT channel from other purchase channels is the higher risk and uncertainty the IoT channel entails for consumers. Even though all the terms and conditions and policies regarding consumer purchases are the same across all shopping channels of the retailer, consumers face higher uncertainty through the IoT channel as a result of the lower information intensity because, for instance, they do not have direct access to recent product reviews, new product releases, and so on. Hence, such uncertainty can affect the product purchase likelihoods accordingly, and this will be reflected in consumers' current and future product demand, as discussed previously. Similarly, there are additional theoretical arguments about why product sales could remain constant, as discussed previously. Therefore, the significance and directionality of the effect of the IoT channel on product sales remain interesting empirical questions, as discussed in Section 1.

3.3. Data Description

Our data set contains information across several markets (i.e., countries) for a period of more than two years—from January 2015 until May 2017—for all the products that became eligible for purchase via the IoT channel of the online retail marketplace (i.e., treated products) in some markets and products that did not become available in this channel. In particular, our data set includes information for all the IoT-eligible products in the markets of the United States, the United Kingdom, Germany, and France; at the time of conducting this study, the IoT channel was adopted for specific products in the United States, the United Kingdom, Germany, and France but not Canada or other markets (see Table 1). Our data set also includes information about these products (i.e., products that were treated in at least one market at some time period) in the markets of the United States, Canada, the United Kingdom, Germany, and France, even if they were not IoT eligible in the specific market (e.g., Canada), because they were available for purchase through the rest of the sales channels; our data set includes information about these products for the complete observation window. Table 1 shows the number of distinct products that became available for purchase through the channel of IoT (i.e., IoT eligible) by each market (i.e., country) and calendar year; all the products that became IoT eligible were already available for purchase through the rest of the sales channels. In particular, there are in total 6,393 unique products that became available through the IoT purchase channel during 2016–2017 in four different markets where the online marketplace operates.[4] The available products for purchase through the IoT channel correspond to a wide range of categories, including grocery, personal care, household, and office products. The price of the products is the same across all the available selling channels of the platform, and there is no additional cost to consumers for using the IoT infrastructure.

Table 1. IoT-Eligible Products by Market and Year

Market	2015	2016	2017	Total
Canada	0	0	0	0
Germany	0	671	164	835
France	0	0	522	522
United Kingdom	0	566	42	608
United States	0	3,402	1,165	4,567
Distinct count	0	4,578	1,887	6,393

Notes. The counts correspond to the number of distinct products that first became eligible for purchase via the IoT channel in the corresponding calendar year for each market. The information for 2017 corresponds to products that became eligible for purchase via the IoT channel until May 2017.

Moreover, our data set is further complemented with information about additional similar products that were not eligible for purchase through the IoT channel (i.e., nontreated products) in any market but could be purchased through the rest of the purchase channels. That is, our data set also includes the nontreated (substitute) products that belong to the same product category and consumers frequently view online when viewing one of the treated products in the same market (McAuley et al. 2015). Hence, our complete data set contains information from several markets for both treated and nontreated control products for the complete observation window. This information for each product in each market includes the product rating, number of user-generated reviews, product price, brand of the product, product category, sales rank, and seller of the product. In summary, our data set includes information from the United States, Canada, the United Kingdom, Germany, and France about (1) treated products before and after the treatment, (2) nontreated products that were treated in other countries, and (3) nontreated products that are similar to treated products in the same market. Figure A3 in the online appendix illustrates these different types of observations in our data set.

Our unique data set enhances the identification of the causal effect of the IoT channel introduction as well as the implementation of several alternative identification strategies as robustness checks. More specifically, our data set enhances the identification strategies described in the following sections based on the variation in both the availability of the IoT devices across countries (i.e., the same product in different markets does not become IoT eligible at the same time, if at all) and the eligibility of the products (i.e., not all products become eligible at the same time, if at all) because of the experimental nature of the introduction of the IoT technology as a direct sales channel. For instance, Finish dishwasher detergent became available in the United States, the United Kingdom, Germany, and France in different months of 2016, whereas Cascade, a similar dishwasher detergent, became available only in the United States, and Method, another similar dishwasher detergent, did not become available for purchase through this channel in any market during our observation window.

Table 2 contains summary statistics that describe the main variables of our empirical model presented in Section 4. The data—apart from the IoT-eligibility information—come from a marketing company in Germany affiliated with Amazon.com. The information on whether, in which market, and during what time period each product became eligible for purchase via the IoT channel was collected from the online marketplace according to the terms and conditions of the corresponding marketplace APIs. Furthermore, additional information comes from Alexa Internet, Inc. (see Section 5.2.5). Finally, as discussed in Section 5.3, we also complement our data set with advertising data that come from the ad intelligence company Kantar Media, data from the analytics company Comscore about sales of other retailers, and other additional sources, as described in Section 5.

4. Empirical Methodology

To formally characterize our econometric model, we model product sales before and after the products become eligible for the IoT sales channel, if they become eligible at all. We undertake several robustness specifications and alternative identification strategies in the following sections, but we first describe our primary identification strategy and econometric specification. Our primary identification scheme relies on panel data and a difference-in-differences (DiD) methodology to measure the causal effect of the IoT. Our main estimating equation for product i in market (i.e., country) c and time period (i.e., day) t is

$$\log(s_{ict}) = \boldsymbol{a}_{ic} + Treatment_{ict}\beta^T + \boldsymbol{X}_{ict}\boldsymbol{\beta}^X + \boldsymbol{Z}_{ict}\boldsymbol{\beta}^Z + \boldsymbol{\tau}_t + \varepsilon_{ict},$$

where s_{ict} is the sales rank of product i in market c in time period t within the corresponding product category, and $Treatment_{ict}$ is a binary variable indicating whether product i was treated in market c in time period t (i.e., if product i was available for purchase via the IoT channel at the corresponding market and time period). The coefficient of main interest, β^T, captures the effect of the IoT on product sales. In our main specifications, we also control for observed time-varying covariates $\boldsymbol{X}_{ict}$, including the (log of the) daily product price, product rating, the (log of the) number of user-generated reviews for the product, and the fraction of solicited reviews for the product, as well as additional controls $\boldsymbol{Z}_{ict}$ such as the seller of the product and public holidays; log denotes the natural logarithm. We also include linear and nonlinear (quadratic) time trends $\boldsymbol{\tau}_t$ (Anagol and Kim 2012, Goldfarb et al. 2015) and product-market-level fixed effects $\boldsymbol{a}_{ic}$, controlling for observed and unobserved heterogeneity. Finally, ε_{ict} is an error term. We also examine several alternative econometric model specifications as well as alternative identification strategies and robustness checks, including a difference-in-difference-in-differences (DDD) methodology (Wooldridge 2010), as described in the following paragraphs. Table 3 presents a summary of the multiple employed identification strategies. Following the extant

Table 2. Descriptive Statistics

Variable	N	Mean	Standard deviation	Minimum	Maximum
Sales rank (log)	13,680,370	9.59	2.08	0	16.07
Treatment (IoT eligible)	13,680,370	0.04	0.19	0	1
Rating	13,680,370	3.33	1.89	0	5
Number of reviews (log)	13,680,370	3.04	2.39	0	9.95
Price (log)	13,680,370	2.91	0.79	−4.60	9.87
Fraction of solicited reviews	13,680,370	0.02	0.10	0	1
Bank holiday	13,680,370	0.30	0.46	0	1

Table 3. Employed Identification Strategies for Causal Inference

Table	Section	Identification strategy	Estimation sample
Table 4	Main results (5.1.1)	DiD (with similar products)	Treated products before and after the treatment and similar nontreated products
Table 5	Main results (5.1.2)	DDD	Treated products before and after the treatment, the same products in other markets, and nontreated similar products
Table 12	Robustness checks (5.3.1)	DDD with PSM	Treated products before and after the treatment, the same products in other markets, and nontreated (matched) products with the same propensity for treatment
Table 13	Robustness checks (5.3.1)	DiD (with the same products)	Treated products before and after the treatment and the same products in other markets

Notes. The products used as similar controls correspond to nontreated products that are similar to the treated products because they belong to the same product category, they are available in the same market, and consumers frequently view them online when viewing one of the treated products. The same products used as controls correspond to products in markets where they are not treated, but the exact products are treated in some other market. Please see the corresponding sections for additional details. DiD, difference-in-differences; DDD, difference-in-difference-in-differences; PSM, propensity-score matching.

literature, sales rank for each product is used as a proxy for demand (e.g., Brynjolfsson et al. 2003, Chevalier and Goolsbee 2003, Ghose et al. 2006, Ghose and Sundararajan 2006, Archak et al. 2011, Gu et al. 2012, Carmi et al. 2017). The model estimation can be performed directly on sales ranks, and the marginal coefficients can be interpreted in terms of changes in sales ranks. The reason for the log specification rather than levels is that the log specification estimates the effect of a change in the independent variables on the percentage change in the dependent variable. This is appropriate because, in our case, as in prior research, there are scale effects (e.g., Chevalier and Mayzlin 2006, Archak et al. 2011, Adamopoulos and Tuzhilin 2015a, Kokkodis and Lappas 2020).

The aforementioned identification strategy enables us to overcome several potential endogeneity challenges. Apart from employing panel data and the DiD methodology for causal inference while controlling for observed and unobserved heterogeneity at the product-market level as described in the previous paragraphs, our identification strategy is further enhanced based on the quasi-experiment induced by the randomness in both the availability of the IoT devices across countries (i.e., the same product in different markets does not become IoT eligible at the same time, if at all) and the randomness in the timing of the eligibility of the products for the IoT channel (i.e., not all products become eligible at the same time, if at all) because of the experimental nature of the introduction of the IoT technology. Beyond the utilized quasi-experiment and panel structure of our data set incorporating several sources of variation (see Section 3.2 and Figure A3 in the online appendix), we also tap into similar (nontreated) control products. More specifically, we use as controls similar nontreated products because these products are perceived as similar and comparable choice alternatives by consumers in accordance with the information-processing theory of consumer search (Bettman 1970). Such controls are based on the products that belong to the same product category and that consumers frequently view online when viewing one of the IoT-eligible products in the same market (McAuley et al. 2015; see also Section 5.1).

In addition, as part of our alternative identification strategy (see Table 3), we use as controls the same (IoT-eligible) products in different markets where they are not IoT eligible (e.g., Canada). That is, we extend the identification strategy from the DiD framework to the DDD framework, and instead of simply using similar products as controls, we also employ as controls exactly the same products (as the treated products) in different markets where they have not been treated (e.g., Canada); this further alleviates concerns regarding any potential differences among IoT-eligible and (non-IoT-eligible) control products (see Section 5.1.2). In particular, this enhanced identification strategy uses the treated products before and after the treatment, these exact products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to the treated products. Nevertheless, the validity of the identification strategies employed is further enhanced by several tests. For instance, we have confirmed the credibility of the standard common trends assumption using testing procedures based on a t-test ($t = 0.6437$; Callaway and Sant'Anna 2018) and group-specific trends ($\beta = 0.0000165$, $p = 0.473$; Angrist and Pischke 2008), and we also validated it based on additional graphical model-free evidence (see Figures A4 and A5 in the online appendix). Finally, we conduct an extensive set of robustness checks, including additional alternative identification strategies and multiple falsification tests, to further enhance our empirical analyses (see Sections 5.3 and 5.4).

5. Results

In Section 5.1.1, we describe the main results of our study and discuss the impact of the introduction of the IoT channel on product sales. Then, in Section 5.1.2, we present the results of the DDD alternative identification strategy. In Section 5.2, we investigate various moderating effects, examining the heterogeneity of the effect under study, and conduct additional analyses that allow us to further understand the IoT demand effects and empirically validate the underlying mechanism. In addition, in Section 5.3, we assess the robustness of our findings by conducting an extensive set of tests and ruling out numerous alternative explanations based on various alternative specifications and identification strategies. Finally, in Section 5.4, we present multiple falsification tests to further validate our findings.

5.1. Main Results

5.1.1. Primary Identification Strategy (DiD). In this subsection, we discuss the estimation results of our empirical model, examining the impact of the IoT channel on product sales. The estimation results presented in this subsection correspond to the first identification strategy using both treated products—before and after the treatment—and nontreated products that are similar to treated products in the same market, as discussed in Sections 3.2 and 4. That is, our main identification strategy is based on the DiD framework (see Table 3); additional identification strategies are presented in the next subsection. In total, this identification strategy employs daily observations from January 2015 to May 2017 corresponding to 15,877 unique products in four different markets (i.e., Germany, France, the United Kingdom, and the United States). Table 4 provides estimates of our main model specifications; the standard errors are clustered at the product-market level to ensure that the estimators are robust to cross-sectional heteroskedasticity and within-panel (serial) correlation (Arellano 1987). In particular, Model 1 examines the impact of IoT introduction on product sales while accounting for the product rating, (log of) the number of user-generated reviews, (log of) the price of the product, and the product seller, as well as product-market fixed effects and nonlinear time trends. Then Model 2 also controls for user-generated reviews solicited by the seller of the product, and Model 3, in addition to the aforementioned variables, controls for holidays, too, in order to capture additional seasonality effects.

Based on the results presented in Table 4, we find that the coefficient of the variable capturing the IoT channel introduction is negative and statistically significant, suggesting that when a product is becoming eligible for IoT purchase, the product's sales increase (i.e., lower sales rank); all the models provide a very good fit to the data. Apart from being statistically significant at the 0.1% level, this effect is also economically significant because the introduction of the IoT technology leads, on average, to an improvement of about 13.92% in sales ranking (i.e., $100 \times (e^{-0.1499} - 1)$). Moreover, note that the coefficients of all the other variables are in accordance with what one would expect and in compliance with the extant literature. Specifically, the coefficient of price is positive and significant, implying that higher product prices increase the sales rank and therefore decrease product sales; if a product price is increased by 1%, the sales rank increases by about 0.64%. The product price in these model specifications is log-transformed because of the wide range of product prices; the results are robust to using the price level or other transformations (e.g., see Section 5.3.4). The estimated coefficient is also in compliance with prior literature (e.g., Chen et al. 2004, Oestreicher-Singer and Sundararajan 2012b). Regarding the average product rating, consistent with Chevalier and Mayzlin (2006), we find a positive effect of the average review rating

Table 4. Estimation Results of Fixed-Effect Models: DiD

Variable	Model 1	Model 2	Model 3
Rating	−0.0323***	−0.0333***	−0.0333***
	(0.0047)	(0.0047)	(0.0047)
Number of reviews (log)	−0.4237***	−0.4321***	−0.4328***
	(0.0109)	(0.0110)	(0.0110)
Price (log)	0.6394***	0.6381***	0.6381***
	(0.0260)	(0.0259)	(0.0259)
Treatment (IoT eligible)	−0.1493***	−0.1492***	−0.1499***
	(0.0070)	(0.0070)	(0.0070)
Fraction of solicited reviews	—	0.5610***	0.5621***
	—	(0.0818)	(0.0818)
Constant	8.9969***	9.0141***	9.0141***
	(0.0810)	(0.0810)	(0.0810)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2058	0.2080	0.2081
Number of observations	10,357,470	10,357,470	10,357,470

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

on the product sales. Specifically, if the average rating is increased by one unit (star; i.e., an increase of about 30% for a product of average rating), the sales rank decreases by 3.28% (i.e., $100 \times (e^{-0.0333} - 1)$). In Section 5.3, we conduct robustness checks allowing for a nonlinear effect of product rating; the results are robust to accounting for nonlinear product-rating effects. Evaluating the rest of the variables in Table 4, we notice that the volume of reviews has a positive effect on product sales as well. In particular, if the number of reviews is increased by 1%, the sales rank improves by about 0.43%. This is consistent with classical models of risk aversion, according to which given two similar products with similar average review ratings, consumers will prefer the product that was reviewed more (Archak et al. 2011). The magnitude of the estimated coefficient is also in compliance with prior literature (e.g., Chen et al. 2004). Interestingly, we also find that a larger fraction of solicited reviews has a negative impact on sales. If the proportion of solicited reviews is increased by 1%, the sales rank deteriorates by almost 0.75% (i.e., $0.01 \times 100 \times (e^{0.5621} - 1)$).

Focusing on the emerging IoT technologies, our paper is the first to study the effect of the introduction of the IoT as an additional sales channel and demonstrates that such a technology adoption enhances the sales of products. Although the extant literature that has examined the effect of the adoption of other sales channel has provided conflicting evidence, our paper reveals that the introduction of IoT technologies, in particular, as an additional sales channel increases product sales; the effect is statistically and economically significant and survives an extensive set of robustness and falsification tests (see Sections 5.3 and 5.4). These findings highlight the business value IoT technologies can have for retailers and brands and offer timely implications for future research.

In addition to the aforementioned findings, in Section 5.2, we delve into the heterogeneity of the effect of the IoT channel and also conduct additional analyses that allow us to better understand this effect and empirically validate the underlying mechanism.

5.1.2. Additional Identification Strategy (DDD). In this subsection, we further enhance our previous identification strategy by extending our analysis to include observations for (control) products that were not treated in the corresponding market but were treated in one of the other markets (i.e., countries). That is, we extend the identification strategy from the DiD framework to the DDD framework (see Table 3), as discussed in Section 4. As before, we also control for various time-varying confounders as well as observed and unobserved heterogeneity at the product-market level.

Table 5 shows the corresponding results for this additional identification strategy. As before, Model 1 examines the impact of the IoT channel on the sales of products while accounting for various time-varying and time-invariant variables. Then Model 2 also controls for user-generated reviews solicited by the seller of the product, and Model 3, in addition to the aforementioned variables, controls for holidays. The results presented in Table 5 corroborate our previous findings (see Table 4) because they remain qualitatively and quantitatively the same. This additional identification strategy reveals that introduction of the IoT technology as a sales channel leads to an improvement of about 13.28% in sales ranking; recall that the estimated effect based on the first identification strategy (DiD versus DDD) we employed in Section 5.1.1 was estimated to be 13.92%.

It is noteworthy that the magnitude of the coefficients of interest is almost the same across the different models and identification strategies, demonstrating the robustness of the findings (see Tables 4 and 5).

In addition to the identification strategies presented in Sections 5.1.1 and 5.1.2, we present additional

Table 5. Estimation Results of Fixed-Effect Models: DDD

Variable	Model 1	Model 2	Model 3
Rating	−0.0236***	−0.0248***	−0.0248***
	(0.0041)	(0.0041)	(0.0040)
Number of reviews (log)	−0.4098***	−0.4171***	−0.4176***
	(0.0099)	(0.0100)	(0.0100)
Price (log)	0.5428***	0.5420***	0.5420***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	−0.1428***	−0.1420***	−0.1425***
	(0.0070)	(0.0070)	(0.0070)
Fraction of solicited reviews	—	0.5374***	0.5380***
	—	(0.0781)	(0.0782)
Constant	9.0895***	9.0989***	9.1008***
	(0.0647)	(0.0647)	(0.0647)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2545	0.2563	0.2563
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.

$^{***}p < 0.001$.

alternative identification strategies as robustness checks in Section 5.3.

5.2. Heterogeneity of IoT Effects

So far, the preceding analyses have demonstrated that the introduction of the IoT as a sales channel leads to a significant improvement in product sales. Focusing on the emerging IoT technologies, our paper is the first to study the effect of the introduction of the IoT as a sales channel and demonstrate that such a technology affects consumers' behavior, enhancing the sales of products. Although the extant literature that has examined the effect of other sales channels has provided conflicting evidence, our paper extends the current literature, making important contributions and yielding timely implications for future research because it is the first study to reveal that the IoT as a sales channel increases product sales; the effect is statistically and economically significant and survives an extensive set of robustness and falsification tests. This contribution is also extended by informing future literature on the heterogeneity of the demand effect of IoT sales channel introduction. The heterogeneity of the effect of the IoT has not been examined in prior literature, similar to the main effect; certain dimensions of heterogeneity have not been examined in prior literature on other sales channels, too. Importantly, the following heterogeneity effect analysis also bolsters the overall contribution of this paper because it further empirically verifies the main identified mechanism and enhances the generalizability of the results. In addition, apart from seeding new future research directions, these analyses and the corresponding findings also highlight the business value of IoT technology for retailers and brands while they offer timely implications, too. In order to leverage the IoT as a sales channel, businesses and practitioners will need to develop sufficient knowledge to make such technology investments.

More specifically, in this section, we delve into the differences in the impact of IoT channel introduction and conduct an in-depth analysis of the aforementioned effect of the IoT channel on sales growth, providing greater insights into the effectiveness of IoT technologies and assessing the underlying mechanism. Such insights can help us better understand which products will the accrue the highest benefits from introduction of the IoT. In particular, we examine the heterogeneity of the effect based on the product price (Section 5.2.1), product taxonomies (Sections 5.2.2 and 5.2.3), degree of product substitutability/differentiation (Section 5.2.4), and new versus existing users (Section 5.2.5), as well as the level of adoption from competitive products (Section 5.2.6).

5.2.1. Product Price. We first examine the moderating effect of price on the effect of the introduction of the IoT channel on product sales. The products that became available for purchase via the IoT infrastructure cover a wide range of price points, and hence, it is important to examine whether more or less expensive products benefit the most from the IoT channel. Moreover, if less expensive products benefit more from IoT, then this would further confirm the identified mechanism, as described in detail in Section 3.1. Alternatively, if more expensive products benefit more, then this would nullify this identified mechanism. Table 6 examines this moderating effect of price on the effect of the introduction of the IoT channel on product sales. Based on these results, we find a positive and significant moderating effect of the product price on the effectiveness of IoT technologies. This finding indicates that less expensive products can more effectively leverage the IoT channel; that is, not only alternatives that are less expensive are more appealing to consumers, but, ceteris paribus, they also can more effectively leverage the additional IoT infrastructure to accomplish efficient commercial transactions while reducing human intervention and largely automating purchase transactions. This finding is in accordance with the main identified mechanism based on mental accounting theory (see Section 3.1) because transaction costs are proportionally higher for low-cost products and, hence, would have a higher impact on cheaper products (Thaler 1985, Kahneman and Tversky 2013). Beyond mental accounting theory and prospect theory, this finding also finds support from extant behavioral research showing that both added shopping convenience and higher product stock availability at home increase consumption quantities more for cheaper products (Chandon and Wansink 2002) because consumer regard time as more important for such products (Eggert and Ulaga 2002, Gupta and Kim 2010). Overall, this finding provides additional empirical support for the underlying mechanism and generates actionable insights for managers.

5.2.2. Search vs. Experience Goods. Moreover, to gain a deeper understanding of the heterogeneity effect and further validate the underlying mechanism, we study whether the product classification of search and experience goods moderates the effectiveness of the demand effect of the IoT channel. The experience versus search goods classification (Nelson 1970, 1974) provides important insights into how consumers' purchase behaviors differ for search and experience goods, and hence, one might expect that IoT channel effectiveness on driving sales growth varies across search and experience goods. As discussed in Section 3.1, if experience goods benefit more from IoT,

Table 6. Heterogeneity of IoT Effect: Product Price

Variable	Model 1	Model 2	Model 3
Rating	−0.0236***	−0.0248***	−0.0248***
	(0.0041)	(0.0040)	(0.0040)
Number of reviews (log)	−0.4096***	−0.4169***	−0.4174***
	(0.0099)	(0.0100)	(0.0100)
Price (log)	0.5418***	0.5411***	0.5411***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	−0.3069***	−0.3008***	−0.3030***
	(0.0320)	(0.0320)	(0.0320)
Treatment (IoT eligible) × *Price* (log)	0.0572***	0.0553***	0.0559***
	(0.0105)	(0.0105)	(0.0105)
Fraction of solicited reviews	—	0.5351***	0.5357***
	—	(0.0781)	(0.0781)
Constant	9.0920***	9.1012***	9.1033***
	(0.0647)	(0.0646)	(0.0646)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2545	0.2563	0.2563
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.
***$p < 0.001$.

then this would also further confirm the identified mechanism. Alternatively, if primarily search goods benefit more, then this would nullify the identified mechanism. Table 7 examines this moderating effect of whether a product is more search or experience good (Nelson 1970).[5] Based on these results, we find a positive and significant moderating effect of the search—versus experience—classification on the effectiveness of the IoT channel. Specifically, the analysis suggests that the introduction of IoT technologies as a sales channel is more effective for experience goods. This interesting finding that experience goods, rather than search goods, are benefiting more from the introduction of the IoT channel further empirically verifies the main identified mechanism of increased purchase convenience and reduced purchase effort (see Section 3.1). This finding is also in accordance with prior literature showing that consumers consider such a reduction of intangible transaction costs more important when shopping for experience goods (Burke 2002) and are willing to spend more time when shopping for search goods (Huang et al. 2009). This is also supported by the theories of Nelson (1970, 1974) and extant empirical research showing that consumers prioritize website and physical-store features that reduce the shopping time for experience goods rather than for search goods (Burke 2002). In addition, this finding is also in compliance with the literature on automaticity because extant research has demonstrated that experience goods typically have lower price elasticity than search goods (Nelson 1970) and that consumers face higher switching costs when evaluating experience goods rather than search goods (Huang et al. 2009), and, thus, they tend to be more loyal to experience goods (Bharadwaj et al. 1993, Dick and Basu 1994). Overall, this finding provides additional empirical support for the main identified mechanism and also unveils important managerial implications for online retailers with regard to how they can strategically leverage IoT technologies because experience goods have traditionally posed a major challenge for online retailers.

5.2.3. Utilitarian vs. Hedonic Goods. Beyond the search versus experience product classification, we extend the heterogeneity analysis of the demand effect of the IoT channel by looking into whether utilitarian or hedonic goods are more likely to benefit more from introduction of

Table 7. Heterogeneity of IoT Effect: Search Goods

Variable	Model 1	Model 2	Model 3
Rating	−0.0236***	−0.0248***	−0.0248***
	(0.0041)	(0.0041)	(0.0040)
Number of reviews (log)	−0.4096***	−0.4169***	−0.4174***
	(0.0099)	(0.0101)	(0.0101)
Price (log)	0.5428***	0.5421***	0.5420***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	−0.1501***	−0.1494***	−0.1498***
	(0.0074)	(0.0074)	(0.0074)
Treatment (IoT eligible) × *Search good*	0.0740***	0.0747***	0.0740***
	(0.0221)	(0.0221)	(0.0221)
Fraction of solicited reviews	—	0.5376***	0.5383***
	—	(0.0781)	(0.0781)
Constant	9.0891***	9.0985***	9.1005***
	(0.0647)	(0.0647)	(0.0647)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2545	0.2563	0.2563
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.

$^{***}p < 0.001$.

such IoT technologies (Hirschman and Holbrook 1982, Dhar and Wertenbroch 2000).[6] This heterogeneity analysis can further help us empirically verify the identified mechanism. In particular, as discussed in Section 3.1, if utilitarian goods benefit more from IoT, then this would further confirm the identified mechanism. Alternatively, if primarily hedonic goods benefit more, then this would nullify the identified mechanism. Table 8 examines the moderating effect of whether a product is more utilitarian or hedonic. Based on these results, we find a negative and significant moderating effect of the utilitarian—versus hedonic—classification on the effectiveness of the IoT channel. In particular, the analysis suggests that the introduction of IoT technologies as a sales channel is more effective for utilitarian goods; that is, the IoT channel is effective for both hedonic and utilitarian goods, with utilitarian products benefiting the most from IoT technologies. Hence, this finding also further supports the main identified mechanism (see Section 3.1) and is in accordance with prior literature showing that consumer purchases of utilitarian goods are significantly influenced by convenience and efficiency (Morganosky and Cude 2000, To et al. 2007) because consumers have a higher willingness to pay in time for hedonic products and consider more important the reduction of intangible transaction costs for utilitarian goods (Burke 2002, Okada 2005). This finding also has managerial significance because it demonstrates in practice the business value of the increased convenience, time efficiency, and closer connection of consumption and purchase phases that IoT technologies offer in retail.

5.2.4. Product Substitutability. In addition, we examine the heterogeneity of the effect of IoT across the level of substitutability (or differentiation) of products. We measure the level of substitutability for each product in each market and time period using a substitutability (differentiation) metric measuring how similar (different) is each product from the rest of available products in the same category, market, and time period based on a textual analysis of the available product information and description (Hoberg and Phillips 2016). For the textual analysis, we use the paragraph vector approach of Le and Mikolov (2014) that employs a neural network to derive a latent representation for each document and then measure

Table 8. Heterogeneity of IoT Effect: Utilitarian Goods

Variable	Model 1	Model 2	Model 3
Rating	–0.0236***	–0.0248***	–0.0248***
	(0.0041)	(0.0041)	(0.0040)
Number of reviews (log)	–0.4098***	–0.4171***	–0.4176***
	(0.0099)	(0.0100)	(0.0100)
Price (log)	0.5428***	0.5421***	0.5420***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	–0.1160***	–0.1142***	–0.1152***
	(0.0151)	(0.0151)	(0.0151)
Treatment (IoT eligible) × *Utilitarian good*	–0.0429*	–0.0445*	–0.0437*
	(0.0212)	(0.0212)	(0.0212)
Fraction of solicited reviews	—	0.5378***	0.5384***
	—	(0.0781)	(0.0781)
Constant	9.0895***	9.0989***	9.1009***
	(0.0647)	(0.0647)	(0.0647)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2545	0.2562	0.2563
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.
$^{*}p < 0.05$; $^{***}p < 0.001$.

the average pairwise document similarity based on the Euclidean distance; here, each product corresponds to a document in our corpus.[7] Intuitively, the textual description is used to assign each product a spatial location based on the product description, generating a Hotelling-like product location space for all available products (Hoberg and Phillips 2016). As discussed in Section 3.1, if more differentiated goods benefit more from IoT, then this would further confirm the identified mechanism. Alternatively, if less differentiated goods primarily benefit more, then this would nullify the identified mechanism. Table 9 presents the corresponding results, examining the moderating effect of the level of substitutability (differentiation) of a product on the effectiveness of the IoT channel. Based on the results, we do find a positive and significant effect. That is, substitutable products benefit less from the introduction of the IoT channel, whereas more differentiated products bene-fit more from the IoT channel. This result is also motivated by the extant literature because consumers exhibit higher loyalty levels and switching costs for more differentiated goods (Dick and Basu 1994) and further validates the main identified mechanism because transaction costs are more prominent for such products.

5.2.5. New vs. Existing Customers. We further extend the analysis of the effect of IoT technologies on demand by examining whether the number of new users in the marketplace drives the effect of the IoT sales channel.[8] Table 10 presents the corresponding results, examining the moderating effect of the number of new users in the marketplace site. Based on the results, we do not find a significant effect on new users. That is, the increase in demand for treated products is not simply due to new users joining the marketplace. This is an interesting finding because it suggests that the increased demand levels of treated products are mainly due to the existing users in the marketplace and not new online consumers or users abandoning competitive websites and joining the marketplace. Notably, this finding is also in accordance with the main identified mechanism of increased purchase convenience and reduced purchase effort as a result of the more direct integration of human actions and

Table 9. Heterogeneity of IoT Effect: Substitutability

Variable	Model 1	Model 2	Model 3
Rating	−0.0233***	−0.0245***	−0.0245***
	(0.0041)	(0.0041)	(0.0040)
Number of reviews (log)	−0.4118***	−0.4192***	−0.4196***
	(0.0100)	(0.0101)	(0.0101)
Price (log)	0.5430***	0.5422***	0.5422***
	(0.0206)	(0.0206)	(0.0206)
Treatment (IoT eligible)	−0.2201***	−0.2185***	−0.2198***
	(0.0228)	(0.0228)	(0.0228)
Treatment (IoT eligible) × *Substitutability*	0.1390***	0.1375***	0.1389***
	(0.0391)	(0.0391)	(0.0391)
Fraction of solicited reviews		0.5407***	0.5413***
		(0.0784)	(0.0784)
Constant	9.0941***	9.1036***	9.1055***
	(0.0650)	(0.0650)	(0.0650)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2600	0.2618	0.2619
Number of observations	13,534,515	13,534,515	13,534,515

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. The additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

the physical world into computer-based purchase systems because prior literature has illustrated that existing users desire convenience and are looking for more time-efficient ways to purchase products compared with new users (Alba and Hutchinson 1987, Avery et al. 2012).

5.2.6. Adoption from Competitive Products. Finally, to fully understand the observed IoT effect, we also examine the effect of the number of treated products on demand levels for competitive treated and control products. Table 11 presents the corresponding results. Based on the results, we find that an increase in the number of treated products (only slightly) decreases the demand of competitive—treated and control—products; the results also remain the same after repeating the analysis on the subsample of control products. However, the estimated coefficient is not statistically significant. Hence, the economic impact on competitive products might not be economically significant. Also taking into consideration the aforementioned findings, this result is particularly important because it demonstrates that the increase in demand for treated products is not simply due to new users in the marketplace or a decrease in demand for competitive products, further suggesting that it is predominantly driven by an increase in demand from existing customers in the marketplace. This finding is also in accordance with the main identified mechanism and the postulated demand effects (see Section 3.1) and separates even more clearly the main mechanism from the additional mechanism of enhanced automaticity because the IoT sales channel does not have an economically significant negative impact on competitive products but enhances the demand for IoT-eligible products.[9]

5.3. Robustness Checks

In this section, we undertake an extensive set of tests to assess the robustness of the results and further strengthen our findings by ruling out competing explanations. The robustness checks we conducted include additional alternative identification strategies (Section 5.3.1), alternative explanations and mechanisms (Section 5.3.2), alternative econometric model specifications (Section 5.3.3), and various other checks (Section 5.3.4). These extensive robustness checks are further supplemented with multiple additional falsification tests presented in Section 5.4.

Table 10. Heterogeneity of IoT Effect: New Marketplace Users

Variable	Model 1	Model 2	Model 3
Rating	−0.0232***	−0.0243***	−0.0243***
	(0.0041)	(0.0041)	(0.0041)
Number of reviews (log)	−0.4066***	−0.4139***	−0.4144***
	(0.0102)	(0.0104)	(0.0104)
Price (log)	0.5406***	0.5399***	0.5399***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	−0.1386***	−0.1379***	−0.1384***
	(0.0069)	(0.0069)	(0.0069)
New users	−0.0004***	−0.0004***	−0.0008***
	(0.0001)	(0.0001)	(0.0001)
Treatment (IoT eligible) × *New users*	0.0002	0.0002	0.0004
	(0.0003)	(0.0003)	(0.0003)
Fraction of solicited reviews		0.5371***	0.5378***
		(0.0798)	(0.0798)
Constant	9.0835***	9.0926***	9.0950***
	(0.0650)	(0.0650)	(0.0650)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2548	0.2565	0.2566
Number of observations	13,542,038	13,542,038	13,542,038

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The *New users* variable corresponds to the increase in the percentage of all internet users who visit the marketplace site in the corresponding market during the last seven time periods. The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

5.3.1. Alternative Identification Strategies. First, we examine additional identification strategies in order to control for any potentially remaining differences between treated and nontreated products. In particular, in addition to the DiD and DDD identification strategies employed so far (see Sections 5.1.1 and 5.1.2, respectively) and even though there are no significant differences between treated and control products in our data set, we also combine propensity-score matching with the DDD identification strategy to further account for any remaining differences between treated and control products. For this robustness check, we use one-to-one matching with replacement and a caliper of 0.01, yielding an absolute standardized mean difference of 0.0312 across all the variables (the absolute standardized median is 0.0167), which ensures that covariate balance has been successfully achieved because the absolute standardized mean difference is well below the strict criterion for identifying adequate covariance balance of 0.1 (Austin 2011). Additionally, we have also examined density distributions of the propensity scores for both treated and control groups, ensuring that there is significant overlap and common support. As before, in all our econometric specifications, we also control for various time-varying confounders as well as observed and unobserved heterogeneity at the product-market level by employing product-market-level fixed effects in our model specifications; please see the notes of Table 12 for additional details. Table 12 presents the corresponding results. The results remain highly robust, further corroborating the aforementioned findings.

As an additional robustness check, we further extend the preceding propensity-score model (PSM) by allowing higher-order terms of the covariates, interaction terms, and lag sales rank—in addition to the rest of the covariates—to determine the propensity for treatment; this PSM approach yields an absolute standardized mean difference of 0.0378 (the absolute

Table 11. Analysis of Effect: Number of Treated Competitive Products

Variable	Model 1	Model 2	Model 3
Rating	−0.0231***	−0.0243***	−0.0243***
	(0.0042)	(0.0042)	(0.0042)
Number of reviews (log)	−0.4224***	−0.4313***	−0.4317***
	(0.0103)	(0.0104)	(0.0104)
Price (log)	0.5566***	0.5557***	0.5557***
	(0.0214)	(0.0214)	(0.0214)
Treatment (IoT eligible)	−0.1516***	−0.1568***	−0.1597***
	(0.0353)	(0.0353)	(0.0353)
Treated competitive products (log)	−0.0013	−0.0005	−0.0005
	(0.0016)	(0.0016)	(0.0016)
Treatment (IoT eligible) × *Treated competitive products* (log)	0.0020	0.0029	0.0033
	(0.0060)	(0.0060)	(0.0060)
Fraction of solicited reviews		0.5809***	0.5815***
		(0.0784)	(0.0784)
Constant	9.0448***	9.0569***	9.0589***
	(0.0676)	(0.0675)	(0.0675)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2600	0.2624	0.2625
Number of observations	13,041,502	13,041,502	13,041,502

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The *Treated competitive products* variable corresponds to the number of products that are treated (IoT eligible) by this time period and belong to the same product category. The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

standardized median is 0.0345). Table A1 in the online appendix presents the corresponding results. The results remain highly robust. Similarly, the results are also robust to using nearest-neighbor matching with the generalized Mahalanobis distance; this matching approach yields an absolute standardized mean difference of 0.0036, ensuring again that the covariate balance has been successfully achieved (the absolute standardized median is 0.0028). The results are also robust to several additional specifications, including also considering in the matching process the time since each product was released.

In addition, to the DiD, DDD, and PSM identification strategies discussed so far, we also employ an additional alternative identification strategy where instead of using similar products as controls, we use as controls only the exact same products (as the IoT-eligible products) in different markets where they have not become IoT eligible during our observation window; this completely eliminates any potential differences among treated and nontreated control products because all the control products are treated in other markets. In particular, this enhanced identification strategy uses the treated products before and after the treatment and these exact products in other markets during the same time period (see Table 3). Table 13 presents the corresponding results based on this additional alternative identification strategy. The results remain highly robust, further corroborating our findings.

These robustness checks are further supplemented with several additional checks discussed in the following subsections. For instance, even though we have used PSM in combination with DDD and the same products in other markets as controls, we also replicate the analysis focusing only on a single market, as discussed in Section 5.3.4. Similarly, as discussed in Section 5.3.4, the results are also robust to using

Table 12. Estimation Results of Fixed-Effect Models Over Matched Sample—DDD with PSM

Variable	Model 1	Model 2	Model 3
Rating	–0.0199***	–0.0213***	–0.0211***
	(0.0049)	(0.0049)	(0.0049)
Number of reviews (log)	–0.3693***	–0.3760***	–0.3768***
	(0.0121)	(0.0121)	(0.0122)
Price (log)	0.5349***	0.5348***	0.5348***
	(0.0200)	(0.0200)	(0.0200)
Treatment (IoT eligible)	–0.1212***	–0.1207***	–0.1214***
	(0.0063)	(0.0063)	(0.0063)
Fraction of solicited reviews		0.5141***	0.5154***
		(0.0898)	(0.0899)
Constant	9.2677***	9.2720***	9.2674***
	(0.0671)	(0.0671)	(0.0671)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2560	0.2577	0.2578
Number of observations	10,985,758	10,985,758	10,985,758

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products and have the same propensity to be treated. The propensity-score matching was conducted based on the propensity scores using the available observable characteristics of the products in our specifications: rating, number of reviews, price, fraction of solicited reviews, product category, market, and the seller of the product. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

Table 13. Estimation Results of Fixed-Effect Models: DiD with Identical Products

Variable	Model 1	Model 2	Model 3
Rating	–0.0027	–0.0005	–0.0005
	(0.0057)	(0.0057)	(0.0057)
Number of reviews (log)	–0.4418***	–0.4601***	–0.4603***
	(0.0141)	(0.0142)	(0.0142)
Price (log)	0.5753***	0.5736***	0.5736***
	(0.0319)	(0.0319)	(0.0319)
Treatment (IoT eligible)	–0.1014***	–0.0981***	–0.0985***
	(0.0064)	(0.0064)	(0.0064)
Fraction of solicited reviews		0.8511***	0.8514***
		(0.0900)	(0.0900)
Constant	8.8151***	8.8393***	8.8403***
	(0.1013)	(0.1011)	(0.1011)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2540	0.2564	0.2565
Number of observations	7,749,984	7,749,984	7,749,984

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated and these products in other markets where they have not been treated. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

observations only from markets that have been established in the literature to be similar in cultural aspects.

5.3.2. Ruling Out Additional Alternative Explanations. Furthermore, in addition to employing the aforementioned identification strategies, we conduct various robustness checks to assess alternative explanations and confounders, including price and marketing promotions (see Section 5.3.2.1), word of mouth (WOM) and novelty effects (see Sections 5.3.2.2 and 5.3.2.3, respectively), other retailers (see Section 5.3.2.4), and potentially nonrandom IoT introduction (see Section 5.3.2.5).

5.3.2.1. Price and Marketing Promotion Effects. One might be concerned that the results might be driven by price promotions or other advertising effects. We evaluate this possibility by capturing the effect of available product price promotions (see Table 14) as well as advertising expenditures in online and offline media (see Table 15). In particular, we first control for the effect of any price-related marketing promotional activities (e.g., electronic coupons, offers, etc.; Adamopoulos and Todri 2014, 2015a) by explicitly controlling for the level of available price discounts, if any. Table 14 presents the results of this robustness check. Based on the results, our findings remain highly robust, alleviating any concerns that the estimated IoT effect is driven by price-related marketing promotional activities. We should also note that the results are also robust to alternative specifications that capture price discounts. For instance, we estimate the percentage of price discounts relative to the regular product price, and we find that our results remain, again, highly robust.

Moreover, another potential alternative explanation might be that the results are driven by online or offline promotional marketing campaigns that are not reflected in the price of the product (Ghose and Todri-Adamopoulos 2016, Ghose et al. 2017, Todri et al. 2020). In order to capture any marketing promotional activities and empirically evaluate this alternative explanation, we further supplement our data set with additional information regarding marketing

Table 14. Estimation Results of Fixed-Effect Models with Price Promotions

Variable	Model 1	Model 2	Model 3
Rating	–0.0236***	–0.0248***	–0.0248***
	(0.0041)	(0.0040)	(0.0040)
Number of reviews (log)	–0.4071***	–0.4143***	–0.4147***
	(0.0099)	(0.0100)	(0.0100)
Price (log)	0.5207***	0.5202***	0. 5202***
	(0.0206)	(0.0206)	(0.0206)
Treatment (IoT eligible)	–0.1451***	–0.1443***	–0.1448***
	(0.0070)	(0.0070)	(0.0070)
Fraction of solicited reviews		0.5258***	0.5264***
		(0.0780)	(0.0780)
Price discount (log)	–0.0359***	–0.0354***	–0.0354***
	(0.0031)	(0.0031)	(0.0031)
Constant	9.1476***	9.1561***	9.1579***
	(0.0647)	(0.0647)	(0.0646)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2571	0.2586	0.2587
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

expenditures. More specifically, we combined our data set with a proprietary data set from the ad intelligence company Kantar Media. This extended data set includes the advertising expenditures (in dollar amounts) in the United States at the brand-week level during our observation period (i.e., 2015–2017). Table 15 presents the results of the robustness check that explicitly controls for both the offline and online advertising expenditures of the product brands; online advertising in the marketplace is captured by a separate variable. Based on the results, all the findings remain highly robust (see Table 15). The advertising expenditures capture a small portion of the previously identified IoT effect because the estimated effect decreased slightly to –0.1353 (Model 3), and the fit of our model specifications is further increased, however, because we see that the IoT effect is not driven by just the promotional marketing campaigns.

5.3.2.2. WOM Effects. In addition, one might be concerned that the estimates regarding the effectiveness of the IoT channel in increasing product sales might be driven by other potential confounders, such as WOM and buzz around IoT technologies (Adamopoulos and Todri 2015b, Adamopoulos et al. 2018). We evaluate this possibility by capturing the effect of market-specific web search trends regarding IoT using data from Google Trends (see Table 16; see also Archak et al. 2011). The results remain highly robust. Based on the results, the web search trends capture a small portion of the previously identified IoT effect because the estimated effect decreased from 13.28% to 12.92%, and the fit of our model specifications is further increased, however, because we see that the IoT effect is not driven by just the buzz around IoT.

The results also remain robust in examining alternative WOM effects. In particular, Table A2 in the online appendix presents the results controlling for trends regarding the particular IoT implementation of the retailer marketplace. The results remain the same after controlling for IoT trends regarding the particular retailer as well. Similarly, the results are the same controlling for trends regarding the news articles in online and offline media mentioning the particular IoT implementation or IoT technologies in general based on the LexisNexis database.

In addition, the results also remain the same after controlling for the number of visitors to the marketplace. Table A3 in the online appendix presents the corresponding results.

5.3.2.3. Novelty Effects. Similarly, we repeat the analysis excluding observations for products that became IoT eligible in the first introduction wave in the corresponding market (see Table 17); note that products became available in the IoT channel in different time periods. This robustness check evaluates whether the sales growth is driven just by the novelty effect, wherein consumers simply purchase these IoT-eligible products in response to enthusiasm or interest for this novel technology. Similarly, the results remain very similar, corroborating the preceding results and further enhancing the robustness of our findings. The results also remain highly robust after excluding additional early adoption waves. The results also remain highly robust after excluding products that became available during the first 60 days of the introduction of the IoT channel or other similar time windows. In addition, the results remain highly robust after including multiple dummies for time since treatment, providing additional evidence that the IoT effect does not vary significantly over time and further alleviating any concerns that the novelty effect might be driving the demand effect of the IoT sales channel (see Figure A6 in the online appendix).

Table 15. Estimation Results of Fixed-Effect Models with Advertising Expenditures

Variable	Model 1	Model 2	Model 3
Rating	–0.0294***	–0.0303***	–0.0303***
	(0.0050)	(0.0050)	(0.0050)
Number of reviews (log)	–0.4557***	–0.4627***	–0.4636***
	(0.0117)	(0.0119)	(0.0119)
Price (log)	0.6040***	0.6027***	0.6027***
	(0.0264)	(0.0263)	(0.0263)
Treatment (IoT eligible)	–0.1374***	–0.1363***	–0.1353***
	(0.0083)	(0.0083)	(0.0083)
Fraction of solicited reviews		0.5784***	0.5796***
		(0.0964)	(0.0964)
Online advertising (log 1,000s)	–0.0050***	–0.0050***	–0.0049***
	(0.0007)	(0.0007)	(0.0007)
Offline advertising (log 1,000s)	–0.0020***	–0.0020***	–0.0020***
	(0.0006)	(0.0006)	(0.0006)
In-marketplace advertising (log 1,000s)	–0.0031	–0.0033	–0.0034
	(0.0018)	(0.0018)	(0.0018)
Constant	9.3961***	9.4074***	9.4108***
	(0.0846)	(0.0845)	(0.0845)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2967	0.2997	0.3001
Number of observations	9,034,774	9,034,774	9,034,774

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The variable online advertising corresponds to the log of online brand advertising expenditures in U.S. dollars (in 1,000s), the variable in-marketplace advertising corresponds to the log of brand advertising expenditures in the marketplace in U.S. dollars (in 1,000s), and the variable offline advertising correspond to the log of offline brand advertising expenditures in U.S. dollars (in 1,000s). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

$^{***}p < 0.001$.

5.3.2.4. Competitive Retailers. Moreover, we also assess the possibility that the identified increase in demand is associated with a change in sales of other retailers. We examine this alternative explanation by conducting a series of robustness checks. In order to capture sales of other retailers and empirically evaluate this alternative explanation, we further supplement our data set with additional information. More specifically, we have combined our data set with a proprietary data set from the marketing and analytics company Comscore. This extended data set includes the sales of other retailers in the United States at the product-retailer-daily level during our observation period. Table 18 presents the results of the robustness check that explicitly controls for the daily sales of each competitive retailer; the competitive retailers are determined based on information from SimilarWeb.com. Based on the results, all the findings are highly robust. The sales of other retailers capture a small portion of the previously identified IoT effect because the estimated effect slightly decreased to –0.1341 (Model 3), and the fit of our model specifications is further increased, however, because we see that the IoT effect is not driven by the sales of other retailers. Besides, the results also robust to determining the set of competitive retailers based on information from the Factiva or Capital IQ databases. Similarly, the results are the same after including all the available retailers in the econometric specifications and not only the competitive ones.

The results are also robust to controlling for the total daily sales of same-category products by other retailers or other competitive retailers. In addition, the results remain the same when controlling for the daily sales of the same product by other retailers, in general, or across the set of competitive retailers.

Table 16. Estimation Results of Fixed-Effect Models with IoT-Related Web Search Trends

Variable	Model 1	Model 2	Model 3
Rating	−0.0219***	−0.0231***	−0.0230***
	(0.0041)	(0.0040)	(0.0040)
Number of reviews (log)	−0.4186***	−0.4265***	−0.4273***
	(0.0100)	(0.0101)	(0.0101)
Price (log)	0.5414***	0.5406***	0.5406***
	(0.0204)	(0.0204)	(0.0204)
Treatment (IoT eligible)	−0.1392***	−0.1382***	−0.1383***
	(0.0070)	(0.0070)	(0.0069)
Fraction of solicited reviews		0.5530***	0.5546***
		(0.0783)	(0.0784)
Web search trends (United Kingdom)	−0.0025***	−0.0026***	−0.0024***
	(0.0003)	(0.0003)	(0.0003)
Web search trends (United States)	0.0001	0.0001	0.0004*
	(0.0001)	(0.0001)	(0.0001)
Web search trends (Germany)	−0.0033***	−0.0034***	−0.0033***
	(0.0004)	(0.0004)	(0.0004)
Web search trends (France)	−0.0026***	−0.0027***	−0.0026***
	(0.0004)	(0.0004)	(0.0004)
Constant	9.1367***	9.1463***	9.1418***
	(0.0646)	(0.0646)	(0.0646)
Product fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2616	0.2639	0.2646
Number of observations	13,680,364	13,680,364	13,680,364

Notes. Panel data analysis with product-market fixed effects, (linear and nonlinear) time trends, and IoT-related web search trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets (nontreated at all time), and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

$^{*}p < 0.05$; $^{***}p < 0.001$.

Nevertheless, we also conduct an additional set of robustness checks where we capture market-specific web search trends for the competitive retailers using data from Google Trends. Table A4 in the online appendix provides the corresponding results. The results again remain highly robust.

5.3.2.5. Nonrandom Treatment. In addition, even though we have employed multiple alternative identification strategies in the main analyses (see Sections 5.1.1 and 5.1.2) and several robustness tests—including propensity-score-matching techniques—to rule out alternative explanations and confounders (see, e.g., Section 5.3.1) in order to further alleviate any potentially remaining endogeneity concerns, we conducted the analysis again excluding observations for products that became IoT eligible in more than one market (see Table 19) because these products could have been strategically selected by the retailer. The results remain highly robust to these checks, too.

Likewise, we also repeated the analysis excluding observations for treated products with an increasing pretreatment sales trend (see Table A5 in the online appendix). As shown in the aforementioned tables, all results corroborate our findings, alleviating any remaining endogeneity concerns. All the robustness checks corroborate our findings because the results remain qualitatively and quantitatively the same. We also conduct additional relevant robustness checks, as discussed in the following section.

Finally, we also control for the historical sales performance of products using a lagged dependent variable econometric specification. Table A6 in the online appendix presents the corresponding results. The results remain highly robust. Similarly, the results are robust to multiple other robustness checks.

Table 17. Estimation Results of Fixed-Effect Models Excluding Observations for the First IoT-Eligible Products in Each Market

Variable	Model 1	Model 2	Model 3
Rating	–0.0213***	–0.0226***	–0.0226***
	(0.0042)	(0.0042)	(0.0042)
Number of reviews (log)	–0.4171***	–0.4248***	–0.4253***
	(0.0101)	(0.0103)	(0.0103)
Price (log)	0.5341***	0.5333***	0.5333***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	–0.1414***	–0.1406***	–0.1405***
	(0.0075)	(0.0075)	(0.0075)
Fraction of solicited reviews		0.5489***	0.5496***
		(0.0784)	(0.0784)
Constant	9.1499***	9.1603***	9.1624***
	(0.0650)	(0.0650)	(0.0650)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2606	0.2622	0.2623
Number of observations	13,237,571	13,237,571	13,237,571

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends excluding observations for the first IoT-eligible products in each market. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. The estimation sample excludes observations for products that became IoT eligible in the first adoption wave in the corresponding market. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

Overall, across a wide variety of robustness checks and alternative specifications, the results further corroborate our findings.

5.3.3. Alternative Econometric Specifications. Moreover, we also examine several alternative econometric specifications of our empirical models. For these robustness checks, we repeat the main analysis presented in Section 5.1.2 with the following alternative econometric specifications. First, we replicate the analysis including just a linear time trend, allowing for unobserved factors to systematically grow or shrink over time—factors essentially unrelated to the main variables of interest that could potentially induce bias in the results (see Table 20). The results further corroborate our findings.

Then we repeat the analysis including year-month fixed effects (see Table A7 in the online appendix), allowing for alternative nonlinear trends that could potentially bias the results while capturing additional seasonality effects. Furthermore, the results also remain robust to employing time fixed effects at more granular levels, such as daily-level fixed effects. Moreover, we further control for domain-specific and product-category-specific nonlinear time trends,

Table 18. Estimation Results of Fixed-Effect Models with Alternative Retailers

Variable	Model 1	Model 2	Model 3
Rating	–0.0290***	–0.0299***	–0.0299***
	(0.0050)	(0.0049)	(0.0049)
Number of reviews (log)	–0.4559***	–0.4628***	–0.4636***
	(0.0117)	(0.0118)	(0.0118)
Price (log)	0.5979***	0.5967***	0.5967***
	(0.0257)	(0.0256)	(0.0257)
Treatment (IoT eligible)	–0.1368***	–0.1357***	–0.1341***
	(0.0083)	(0.0083)	(0.0083)
Fraction of solicited reviews		0.5751***	0.5760***
		(0.0963)	(0.0964)
Alternative retailer A	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer B	0.0001***	0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer C	–0.0000***	–0.0000***	–0.0000***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer D	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer E	–0.0001***	–0.0001***	–0.0001***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer F	0.0016***	0.0016***	0.0012***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer G	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer H	–0.0000***	–0.0000***	–0.0000**
	(0.0000)	(0.0000)	(0.0000)
Alternative retailer I	–0.0004***	–0.0004***	–0.0003***
	(0.0000)	(0.0000)	(0.0000)
Constant	9.3897***	9.4001***	9.3991***
	(0.0823)	(0.0823)	(0.0823)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.3143	0.3174	0.3176
Number of observations	9,176,608	9,176,608	9,176,608

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, the seller of the product, and the sales units of other retailers. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

Table 19. Estimation Results of Fixed-Effect Models Excluding Observations for Products that Were Treated in More Than One Market

Variable	Model 1	Model 2	Model 3
Rating	−0.0232***	−0.0244***	−0.0244***
	(0.0041)	(0.0041)	(0.0041)
Number of reviews (log)	−0.4109***	−0.4183***	−0.4188***
	(0.0101)	(0.0102)	(0.0102)
Price (log)	0.5373***	0.5365***	0.5365***
	(0.0206)	(0.0205)	(0.0206)
Treatment (IoT eligible)	−0.1428***	−0.1420***	−0.1424***
	(0.0071)	(0.0071)	(0.0071)
Fraction of solicited reviews		0.5351***	0.5357***
		(0.0789)	(0.0789)
Constant	9.1288***	9.1382***	9.1402***
	(0.0649)	(0.0649)	(0.0649)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2592	0.2609	0.2610
Number of observations	13,347,445	13,347,445	13,347,445

Notes. Panel data analysis with product-market fixed effects and (linear and nonlinear) time trends for products excluding observations for products that were treated in more than one market. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets (nontreated at all time), and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

Table 20. Estimation Results of Fixed-Effect Models with Linear Time Trend

Variable	Model 1	Model 2	Model 3
Rating	−0.0215***	−0.0227***	−0.0227***
	(0.0040)	(0.0040)	(0.0040)
Number of reviews (log)	−0.4177***	−0.4251***	−0.4256***
	(0.0098)	(0.0099)	(0.0099)
Price (log)	0.5427***	0.5419***	0.5419***
	(0.0205)	(0.0205)	(0.0205)
Treatment (IoT eligible)	−0.1374***	−0.1367***	−0.1371***
	(0.0069)	(0.0069)	(0.0069)
Fraction of solicited reviews		0.5481***	0.5489***
		(0.0783)	(0.0783)
Constant	9.0292***	9.0397***	9.0405***
	(0.0647)	(0.0647)	(0.0647)
Product-market fixed effects	Yes	Yes	Yes
Additional product controls	Yes	Yes	Yes
Time trend (linear)	Yes	Yes	Yes
Additional controls	No	No	Yes
R^2	0.2549	0.2565	0.2566
Number of observations	13,680,370	13,680,370	13,680,370

Notes. Panel data analysis with product-market fixed effects and linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market in which they were treated, these products in other markets where they have not been treated, and nontreated products (in the same market) that are similar to treated products because they belong to the same product category and consumers frequently also view them online when viewing one of the treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The product controls include the brand of the product, the product category, and the seller of the product. Additional controls include controls for bank holidays. Robust standard errors are reported.

***$p < 0.001$.

allowing for more flexible patterns in the time trends that could vary across countries and product categories, respectively (see Tables A8 and A9 in the online appendix). All the results corroborate our findings. The results are also robust to including separate product, market, and time-period (i.e., day) fixed effects (see Table A10 in the online appendix).

5.3.4. Additional Robustness Checks. Furthermore, we also conduct additional robustness checks to further assess the possibility that the aforementioned findings are capturing other factors instead of the effect of the IoT channel on demand levels. As part of these robustness checks, we repeat the analysis including only observations with a product price less than or equal to $100 in order to examine the robustness of results to outliers in terms of product price and pricing mistakes (see Table A11 in the online appendix). The product price in these results does not need to be log-transformed as before (Chen et al. 2004, Gu et al. 2012, Oestreicher-Singer and Sundararajan 2012a, Oestreicher-Singer and Sundararajan 2012b) because of the limited price range here. The results remain highly robust, as shown in Table A11 in the online appendix. Similarly, the results are robust to also excluding any products with a price lower than $10; in addition to pricing mistakes and outliers, this also alleviates any concerns regarding accidental purchases driving the estimated effect (see also Section 3). The results are also robust to variable transformations, too. We have also conducted an additional robustness check by transforming all the prices from the local currencies into U.S. dollars. Table A12 in the online appendix presents the results of the aforementioned robustness check. The results remain highly robust, further corroborating our findings.

In addition, we also control for nonlinear effects of product ratings by employing dummy variables for different ranges of product ratings (see Table A13 in the online appendix) instead of average consumer ratings (Forman et al. 2008, Mudambi and Schuff 2010). The baseline level corresponds to products with no ratings, and hence, this specification also controls for products that might not have any consumer reviews. The results remain highly robust again.

Moreover, in order to explicitly capture any heterogeneity across markets, we build a random coefficients model. Table A14 in the online appendix presents the results of this random coefficients model. We notice that the effect of the IoT sales channel remains robust after accounting for the heterogeneity of the treatment effect across markets. Similarly, the results are robust to multiple other robustness checks, too. For instance, we conduct a subsample analysis by focusing on countries that have been established in the literature to be similar in cultural aspects (i.e., the United States and Canada; Foerster and Karolyi 1993). Finally, we also replicate the analysis focusing only on a single market (i.e., the United States) in order to enhance the homogeneity of the data set (see Table A15 in the online appendix). All the robustness checks corroborate our findings because the results remain qualitatively and quantitatively the same.

5.4. Falsification Tests

To further assess the robustness of our findings, we conduct various falsification tests (placebo studies) using the same econometric models as earlier (in order to maintain consistency) but randomly indicating (1) which products were eligible for purchase via the IoT channel (i.e., random product), (2) when they became eligible (i.e., random time period), and (3) where they became eligible (i.e., random market), as well as (4) examining the impact of the actual treatment on an outcome that should be theoretically unaffected by the treatment (i.e., placebo outcome). The results of these falsification tests are shown in Tables A16–A20 in the online appendix. Specifically, Table A16 shows the results of the falsification test randomly indicating which products were treated in which market and in what time period. Table A17 shows the results of the falsification test randomly indicating for treated products in which market and in what time period each product was treated (i.e., random market and time period). Table A18 shows the results of the falsification test randomly indicating for treated products and the time period they were treated in which market they were treated (i.e., random market). Table A19 shows the results of the falsification test randomly indicating for treated products in the market they were treated what time period they were treated (i.e., random time period before the actual treatment, if any). Table A20 shows the results of the falsification test examining the impact of the actual treatment in one of the markets with treated products (see Table 1) on the corresponding outcome in the market of Canada, which should be theoretically unaffected because no product was treated there (i.e., placebo outcome). We see that under these extensive falsification checks, the corresponding effects are not statistically significant, indicating that our previous findings are not a statistical artifact of the econometric specifications and further validating that we have indeed estimated the actual demand effects of the IoT sales channel.

6. Discussion and Implications

The IoT is rapidly becoming one of the most popular emerging technologies in business and society. Given the unprecedented opportunities the IoT generates for brands and retailers, it is important to glean timely insights regarding the business value of the IoT and understand whether the introduction of an IoT technology into the set of available purchase channels for consumers affects the sales of physical products. In this study, using empirical data from a multinational online retailer that introduced an IoT sales channel and using a quasi-experimental research design, we examine the effect of the introduction of IoT technology on product sales and demonstrate the demand effects of the IoT. In addition, we conduct additional analyses of the IoT effect and also delve into the effect heterogeneity, examining various important moderating effects on the impact of the IoT and empirically validating the underlying mechanism of the effect of the IoT sales channel. All the findings of our econometric analyses are highly robust and have survived a wide range of alternative identification strategies, robustness checks, and falsification tests. To the best of our knowledge, this is the first paper to study the impact of the IoT on product sales. Our research makes several important contributions to the extant literature. First, this work makes important contributions to the literature of sales channels. The impact of IoT technologies still has not been investigated despite the distinct characteristics of IoT technologies and their potential to transform consumers' behavior. Our paper is the first to study the effect of the introduction of the IoT as a sales channel and demonstrates that the adoption of such a technology enhances the sales of eligible products in the marketplace. Besides, the findings of this study inform future literature of the heterogeneity of the demand effects of IoT adoption. Our findings reveal, among other things, that less expensive and more differentiated products as well as experience and utilitarian goods can accrue higher benefits leveraging more effectively novel IoT technologies. The heterogeneity of the effect of the IoT has also not been examined in prior literature, similar to the main effect. In addition, certain dimensions of heterogeneity have not been discussed in prior literature on other sales channels. For instance, to the best of our knowledge, prior literature has not investigated the moderating effect of the level of product differentiation on the impact of the introduction of a new sales channel. Beyond the extant literature on sales channels, our results also have implications for the literature on mental accounting theory. For instance, our results posit that a technological development affecting the efficiency, ease, and speed at which products can be purchased—lowering intangible transaction costs—could be a useful means of adjusting the mental accounting of consumers and thus changing consumers' consumption patterns as depicted by product demand levels. This underlying mechanism has been empirically validated in multiple ways. Moreover, the impact of mental accounting can be heterogeneous across levels of product differentiation, as illustrated through the demand effects of the IoT. To the best of our knowledge, prior literature has not examined such effects. The implications of this research also extend beyond the IoT channel because the findings also inform the literature on firm and retailer competition. For instance, our findings suggest that lowering the purchase effort and increasing the purchase convenience by integrating human actions and the physical world into computer-based purchase systems through the IoT sales channel increase product demand, similar to a reduction in tangible costs. Hence, the streams of literature examining retailer competition and competition on marketplaces—vis-à-vis traditional price and location competition—should also examine the competition of retailers across the intangible dimensions of convenience and effort enabled by novel technological developments and IT artifacts.

Beyond the aforementioned theoretical contributions, the findings of this study also have important managerial implications. For instance, we find that IoT technologies have a positive effect on sales growth. This effect is both statistically and economically significant. In addition, this is an important and timely finding for managers because we are still in the early stages of deployment of IoT technologies, and knowledge of the effect of the IoT channel is important for determining the attractiveness of investments in IoT technologies. Our findings show the potential of such IoT investments and suggest that retailers and marketers should invest in IT because of the significant positive impact of these technologies on product sales.

Similarly, the additional analyses of the demand effects we examined in this study contribute to other insights into consumer behavior and a more detailed understanding of the heterogeneity of the effectiveness of the introduction of IoT technologies in the retail industry. Such moderating effects are also important for managers because they provide actionable insights and help businesses further understand which products would accrue the highest benefit from such innovations and which would benefit the least. Therefore, the results of this study showcase to digital retailers how they can better capitalize on the novel IoT technologies. For instance, the results of this study illustrate that IoT technologies can be effectively used to promote sales of experience goods, which can be a major hurdle for online retailers (Nelson 1970, Klein 1998). In addition, these findings can contribute to more accurate product sales predictions for retailers, leading to more efficient supply chain operations.

Beyond the aforementioned managerial implications, the IoT channel we examined and the corresponding findings of this study can inform several other managerial decisions and practices regarding future embodiments of IoT and other relevant technologies enhancing convenience and largely automating the purchase process. More specifically, the IoT technology we examined allows the collection of data at the time of usage of physical products. Such granular information can enable retailers and platforms to tap into consumption analytics (Adamopoulos 2013a, Adamopoulos and Tuzhilin 2013, 2015b), moving beyond just purchase analytics, and better address the evolving needs of consumers while exploiting additional revenue opportunities. In particular, the information about when products are used and in what combinations can allow for accurate early prediction and further automation of product replacement, upgrade, replenishment, or bundling of products based on their exact usage patterns. Similarly, rich product usage knowledge based on IoT devices can further facilitate time-sensitive cross-selling marketing, including advertisements and promotions at the time of consumption of physical products. Finally, such IoT devices can also issue health or security alerts based on patterns of consumption of products (e.g., when a product is consumed after the expiration date or beyond recommended limits; Natarajan and High 2017). Nevertheless, there are several actions retailers may take to fully realize the potential of the IoT. Specifically, retailers might need to implement security and encryption protocols to effectively protect any sensitive consumer information. Similarly, retailers may employ integrated information systems and increase security by not requiring consumers to provide again any sensitive information already available in other purchase channels. In the same fashion, in order to entirely harness the potential of the IoT channel, retailers should foster trust in consumers by adapting their policies to the new channel. For instance, retailers might offer free returns for products purchased through the IoT. Lastly, to maximize the returns on the IoT, retailers can also offset any potential IoT barriers by offering the option for consumers to directly get fully preconfigured IoT devices, as well as by effectively communicating the usefulness and ease of use of the IoT sales channel (Pavlou and Fygenson 2006).

Finally, beyond the theoretical and managerial implications discussed herein, this study also has the potential to seed several new interesting research directions. For instance, future research could examine additional moderating effects on the relationship of the IoT and sales growth to further enrich our understanding of the impact of IoT technologies on retailing. Moreover, future research could examine the business value of IoT technologies in other industries and verticals, as well as specific cross-channel effects of the IoT. Lastly, given the significant impact of the IoT sales channel on product demand, it would be interesting for future research to further investigate the impact of other technological artifacts on consumer behavior, including additional internet-connected devices. Because of the short lifecycle of high-tech products and the constructive destruction practices of companies (Levitt 1965, Lu and Marjot 2008), current IoT devices are superseded by newer interface-free models and services, including voice-activated ones. Given the theoretical foundations of this study and the empirical analyses we conducted, the findings should generalize well to other IoT devices that adjust the mental accounting of consumers by decoupling purchases and payments (making payments less salient) and enhancing the efficiency, ease, and speed at which products can be purchased (lowering intangible transaction costs by enhancing the convenience and reducing the effort of making a purchase), and we hope that our research will seed new, exciting research directions for devices with alternative characteristics (Lauterborn 1990, Alba et al. 1997, Verhoef et al. 2007).

Although this paper has taken important steps toward studying the demand effects of IoT technologies in retailing, we acknowledge that there are several limitations in our analysis, mostly emerging from data-availability issues. One of the limitations of this study is that we have access to data corresponding to a single multinational online marketplace. Another limitation of our data set is that some of the products are not available in all markets. Our data set is also limited to aggregate daily data and not at a more granular level. Similarly, because of privacy concerns, we do not have access to consumer-level statistics. Despite these limitations, our contributions inform the current literature in important ways and may also be widely relevant to managers while also seeding a number of new directions for future research. Our hope is that these limitations will pave the way for future research.

7. Conclusions

In this study, using empirical data from a multinational online retailer that introduced an IoT sales channel and employing a quasi-experimental research design, we study the effect of the introduction of the IoT on product sales and demonstrate the business value of the IoT for retailers and brands. Our analyses reveala statistically and economically significant increase in sales owing to the introduction of IoT technology as a sales channel.

In addition, we conduct additional analyses of the IoT effect and also delve into the effect of heterogeneity, examining important moderating effects on the impact of the IoT channel, such as the price of the product and whether the product is more a search or experience good, as well as whether it is a hedonic or utilitarian good. The corresponding analyses also empirically validate the underlying mechanism supported by the mental accounting theory. Our findings reveal that less expensive products and more differentiated as well as experience and utilitarian goods, rather than search or hedonic goods, can accrue the highest benefits, leveraging more effectively the novel IoT channel. Our findings also show that the increase in demand is mainly because of increased demand levels from the existing customer base of the retailer marketplace.

We also conduct an extensive set of robustness checks and falsification tests to further validate our analysis. All the results corroborate our findings, further strengthening our contribution. To the best of our knowledge, this is the first paper to study the impact of an IoT technology on product sales, drawing significant theoretical and managerial implications while seeding future research directions for devices and technologies largely automating the purchase process.

Acknowledgments

The first two authors contributed equally and are listed in alphabetical order.

Endnotes

[1] Apart from designing the IoT devices, the marketplace has also designed and configured the corresponding APIs and the backend infrastructure required for the IoT channel. For instance, the marketplace also provides end-to-end encryption and device certificates.

[2] An additional policy to prevent any potential accidental purchases is that the marketplace allows one order per product and customer at a time to be out for delivery.

[3] During this initial setup of the IoT devices by the consumers, each IoT device is also registered to the consumer's account in the platform through the IoT device's uniquely identifiable serial number and obtains access to the consumer's username and password, credit card information, delivery address, and so on. This initial setup of the IoT device mainly entails simply connecting to Wi-Fi and providing the username and password and is completed through a connection based on one of the aforementioned modules (i.e., Wi-Fi, Bluetooth, or ultrasound) and the mobile app of the marketplace. Put simply, the initial setup consists of a few simple steps and can be completed by consumers in just a few seconds, as described in this section. The consumers can also directly get partially preconfigured IoT devices from the online marketplace. Such preconfigured devices are already configured to purchase certain products. After their configuration, all IoT devices purchase a single (eligible) product.

[4] The online marketplace also operates in the market of Canada, but IoT technologies were not adopted yet in this market at the time of this study.

[5] Because products involve a bundle of search and experience attributes, the literature suggests that search goods are products whose attributes that are most important to assessing product quality are generally discoverable prior to purchase, whereas experience goods are products whose attributes that are most important to assessing product quality are generally discoverable only after consuming or experiencing the products (Huang et al. 2009). The products were classified into search and experience goods by three independent research assistants based on 1 (= purely experience) to 7 (= purely search) Likert scale questions following the extant literature (Huang et al. 2009). We examined the degree of agreement among the three raters with Krippendorff's alpha coefficient, and we found that there is a high average interrater reliability of 0.927. The average score of the search products was 5.85. The empirical results remain robust to classifying as search (experience) only products that were rated very high (low)—that is, an average of six or higher (two or lower) instead of above (below) four, which is the median of the scale) in the corresponding scale.

[6] Utilitarian goods are dominantly purchased for their practical uses and are based on the consumers' needs, whereas hedonic goods primarily allow the consumer to feel pleasure, fun, and enjoyment from buying the product (Hirschman and Holbrook 1982, Wertenbroch et al. 2005). The products were classified into hedonic and utilitarian goods following the extant literature, as described earlier (Dhar and Wertenbroch 2000). We examined the degree of agreement among the three raters with Krippendorff's alpha coefficient, and we found that there is a high average interrater reliability of 0.941. The average score of the utilitarian products was 5.35. The empirical results remain robust to classifying as utilitarian (hedonic) only products that were rated very high (low) in the corresponding scale.

[7] The methods employed for latent space representations and its variants have been thoroughly evaluated in Mikolov et al. (2013a, b) and Le and Mikolov (2014) and outperform several other deep-learning methods and architectures, including deep convolutional (Collobert and Weston 2008) and recurrent neural networks (Mikolov et al. 2013a, c). Note that this method is general and applicable to texts of any length (e.g., phrases, sentences, paragraphs, documents, etc.) and does not require task-specific tuning, nor does it rely on additional methods such as parse trees (Le and Mikolov 2014). In addition, compared with traditional bag-of-words models (e.g., TF-IDF) that only work in terms of discrete units without meaning that have no inherent relationship to one another (Mikolov et al. 2013c), the method we employed does not suffer from data sparsity and high dimensionality (Le and Mikolov 2014, Joulin et al. 2016).

[8] The additional information on the number of new users in the marketplace site and the percentage of all internet users who visit the site used in these specifications is from Alexa Internet, Inc.

[9] Beyond validating the identified mechanism based on econometric analysis, we also examined qualitative data. The identified mechanism also finds further support in the comments of consumers in their reviews phrases, such as "in-home convenience," "super convenience," "ease of purchasing," "so simple," "easy," "value time," "don't have to think at all," and "automatically," describing their experience with the IoT devices. The underlying mechanism is also confirmed after the analyses based on conversations with consumers (Adamopoulos 2013b).

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