# Demand Effects of the Internet-of-Things Sales Channel

*Completed Research Paper*

**Panagiotis Adamopoulos**
Goizueta Business School
Emory University
padamop@emory.edu

**Anindya Ghose**
Stern School of Business
New York University
aghose@stern.nyu.edu

**Vilma Todri**
Goizueta Business School
Emory University
vtodri@emory.edu

## 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 utilize 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 demand effects of IoT and understand whether the adoption of an IoT technology as an alternative purchase channel for consumers affects the sales of physical products. In this paper, using empirical data from an online retailer who adopted an IoT technology that largely automates the consumers' purchases and utilizing a quasi-experimental framework, we study the effect of the adoption of the IoT channel on product sales. Our analyses reveal a statistically and economically significant increase in sales as the result of adopting an IoT technology and demonstrate the business value of IoT for retailers and brands. Besides, we delve into the effect heterogeneity by examining the impact of IoT for products in different price ranges and different product categories (i.e., search versus experience goods). Our analyses reveal that less expensive products as well as experience goods, rather than search 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 managerial implications and future research directions.*

**Keywords:** Internet of Things, electronic commerce, sales growth, retailing, econometrics

## 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 enables 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 (Ericsson 2017; Evans 2009) while business IoT spending is forecasted to reach almost $3 trillion (Gartner 2017) positioning the IoT as potentially one of the biggest IT evolutions of our time. It has also been estimated that IoT will have a great impact on the economy by facilitating new business models, improving efficiency, and generating new forms of revenue (Al-Fuqaha et al. 2015).

One way IoT technologies 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. For instance, in such an IoT-enhanced shopping future in the retail industry, Internet-connected devices could largely automate the purchase of everyday items on behalf of consumers with reduced human interaction. Some retailers and brands have already begun to leverage IoT in order to minimize consumer interaction and enhance customer experience (Evans 2017). Amazon is an example of utilizing IoT technologies for product purchases (Greenfield 2017). Such largely automated consumerism can generate tremendous opportunities for brands and retailers as it makes the purchasing process more frictionless and convenient, which could ultimately foster consumers' loyalty towards the corresponding brands and retailers.

Despite the promising opportunities of IoT technologies, 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 business benefits as the top overall challenge to the adoption of IoT technologies (Brand and Geschickter 2016). Similarly, a survey by eMarketer indicates that 37% of 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 unpreceded 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 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 the IoT technology as an alternative purchase channel could decrease product sales due to 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 over-purchasing or stockpiling behavior of consumers due to lower expected future transaction costs. That is, allowing consumers to order products with reduced human interaction through IoT technologies might result in a reduction in presently purchased quantities due to lower expected future transaction costs. Similarly, a reduction in product sales might occur due to 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, the introduction of IoT technologies in the purchase process may positively impact product sales. An increase in product sales could occur due to the convenience of this purchase channel for consumers. Besides, introducing IoT technologies that enable product purchases with minimum human interaction might result in increased consumer inertia and reduced variety-seeking behaviors; consumers might not reevaluate their product and brand choices in future orders, leading to increased consumer loyalty towards 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 an IoT channel on product sales remains an empirical question of paramount importance. Beyond 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. Finally, it is of paramount importance for managers and retailers to also understand what types of products accrue the highest benefits. Thus, conducting an in-depth analysis of the IoT effect can help businesses and practitioners make better technology investments and efficiently leverage the Internet of Things 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 adoption 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 examining important moderating effects of this relationship. Specifically, we investigate whether the price of a product as well as whether the product is a search or an experience good moderate the effectiveness of the IoT technology adoption on product sales. Our analyses reveal interesting findings that demonstrate the demand effects of the IoT sales channel. These findings, apart from statistically and economically significant, are also timely. In particular, this is the first paper to study the impact of an IoT technology on product sales and, thus, this paper contributes 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.

## Literature Review and Research Questions

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

More specifically, some of the aforementioned studies have documented that the addition of such 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 while 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 when a store opens locally people substitute away from online purchasing while 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. 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 adoption of a mobile channel increases product sales. Likewise, Liu et al. (2016) find that such an adoption of a mobile channel increases consumers' demand for digital services. Delving into the adoption of a tablet sales channel, Xu et al. (2016) find that the introduction of tablets enhanced the overall growth of a retailer's e-commerce sales.

Nevertheless, as depicted in the product purchase process described in detail in the next section (see Figures 1 and 2), the IoT channel exhibits several differences from existing sales channels as it reduces human interaction in the purchasing process and more directly integrates human actions and the physical world into computer-based systems. In particular, IoT reduces the time as well as the cognitive and physical effort involved in purchasing a product and, hence, consumers face a lower (non-monetary) transaction cost when they shop through the IoT channel. However, at the same time, the IoT channel also reduces consumers' potential enjoyment and pleasure derived from the shopping process, compared to other traditional channels utilized by retailers. In addition, another difference of the IoT channel from other purchase channels is the higher risk the IoT channel entails for consumers due to the lower information intensity. Such characteristics of IoT constitute this novel sales channel significantly different from other previously studied channel. Hence, the effect of the IoT channel on product sales remains an empirical question of paramount importance.

Thus, extending current literature on Information Systems and IoT, this paper studies the effect of the adoption of an IoT technology as a purchase channel on product sales and demonstrates the business value of IoT for retailers and brands. Further delving into the effectiveness of IoT technologies on sales growth, we also examine important moderating effects of this relationship. In particular, we study the following research questions:

- **RQ 1**: Does the introduction of an IoT technology into the consumers' purchase channel sets affect the product sales?
- **RQ 2**: Is the effectiveness of the introduction of an IoT technology into the consumers' purchase channel sets on product sales heterogeneous for different product attributes?

This is the first paper to study the impact of the IoT-enabled sales channel on product sales and, 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 (Adamopoulos and Tuzhilin 2015) as well as the emerging literature on IoT technologies (Minerva et al. 2015). The contribution of this paper is further enhanced by examining important moderating effects of the relationship of IoT technologies with sales growth and, hence, strengthening 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 firms and future research.

## Empirical Background and Data Description

In the following section, we describe the empirical setting for our study and the product purchase process through the novel IoT sales channel. Then, Section 'Data Description' describes the dataset used in our empirical analyses to study the effect of the adoption of the IoT-enabled channel on product sales.

### *Product Purchase Process via the IoT Channel*

The newly adopted IoT channel enables customers and retailers to transform the traditional product purchase process reducing human interaction. In our setting, thanks to the introduction of the IoT channel, orders for the product purchases can be placed on the online retailer marketplace by the IoT devices (see Figure 1). These IoT devices constitute the relevant "things" from a user and application perspective in the IoT system of our setting (see Figure 2). The IoT devices are connected to the retail marketplace via the Internet through a required Wi-Fi connection -provided by the consumer- that gives to IoT devices the necessary access to the Internet, the second component in the IoT system of our setting.

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 "Internet of Things" (Minerva et al. 2015) and the purchase process in our empirical setting (see Figure 1). More specifically, as illustrated in Figure 2, 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 the successful completion of the product orders and other functions. In addition to the aforementioned connectivity modules, the IoT devices also embed a sensor/actuator (Minerva et al. 2015). When the sensor/actuator is triggered, the IoT device utilizes the embedded intelligence and knowledge functions as tools in order to make requests/calls directly to the marketplace APIs to place an order based on the 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 any purchase terms on behalf of the consumer, offer security intelligence, etc.[1,2]

Such orders placed by the IoT device for the consumer utilizing the embedded intelligence and knowledge functions are then fulfilled without the need for the consumer to take any further actions, such as inspecting the purchase terms and conditions, providing credit card information, delivery address, confirming the purchase, etc. Similar to other sales channels, 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 and there is no additional cost to the consumers for utilizing the necessary IoT infrastructure; the price of the products is the same across all the available selling channels of the platform.

Figure 1 offers a schematic representation of the product purchase process via the IoT channel described above and Figure 2 illustrates the main components of an IoT device chip.

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[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.

[2] The initial setup of the IoT devices is completed through a mobile app or the corresponding website of the retail platform, where a consumer can register each device to her/his account in the platform through the IoT device serial number or a connection based on one of the aforementioned modules (i.e., Wi-Fi, Bluetooth, or ultrasound) and the mobile app of the marketplace.

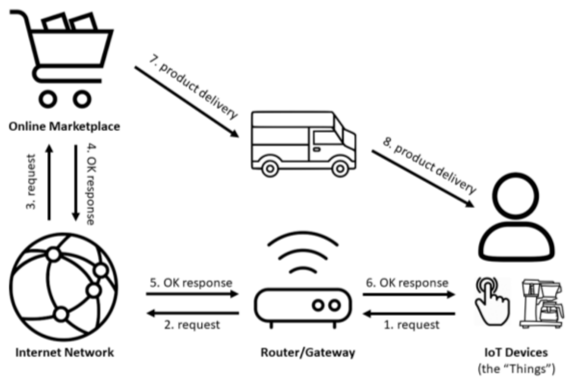


**Figure 1. Schematic representation of the product purchase process via the IoT channel**

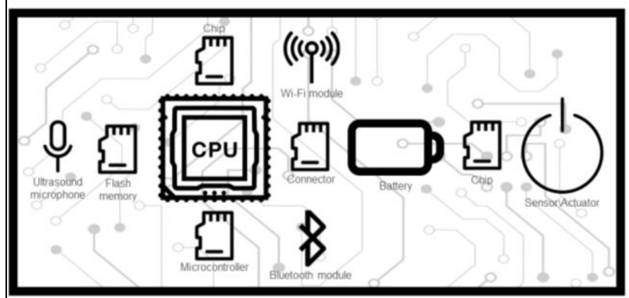


**Figure 2. Schematic representation of the main components of the IoT device chip**

The available for purchase through this sales channel products correspond to a wide range of categories including grocery, personal care, household and office products, etc. 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 of the online retailer. 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. The online marketplace also operates in the market of Canada but IoT technologies were not adopted in this market at the time of conducting this study. The next paragraph describes in detail our dataset.

**Table 1: IoT Eligible Products by Market and Year**

| Market | 2016 | 2017 | Total |
|---|---|---|---|
| **Canada** | 0 | 0 | 0 |
| **Germany** | 671 | 164 | 835 |
| **France** | 0 | 522 | 522 |
| **United Kingdom** | 566 | 42 | 608 |
| **USA** | 3402 | 1165 | 4567 |
| **Distinct count:** | 4578 | 1887 | 6393 |

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.

## *Data Description*

Our dataset contains information across several markets (i.e., countries) for a period of over two years –from January 2015 until May 2017– for both all the products that became eligible for purchase via the IoT channel of the online retail marketplace (i.e., treatment) in some market and products that did not become available in this channel. In particular, our dataset includes information for all the treated products in the markets of USA, United Kingdom, Germany, and France; at the time of conducting this study, the IoT channel was adopted for specific products in USA, United Kingdom, Germany, and France but not Canada or other markets (see Table 1); the available for purchase products correspond to a wide range of categories including grocery, personal care, household and office products, etc. Our dataset is complemented with information from the markets of USA, Canada, United Kingdom, Germany, and France about these products (i.e., products that were treated in at least one market at some time period) also in the markets that were not treated. Moreover, our dataset is further complemented with information about additional (similar) products that were not eligible for purchase through the IoT channel (i.e., non-treated) in any market but could be purchased through any of the rest of the purchase channels. That is, our dataset also includes the non-treated products that belong to same product category and consumers frequently view online when viewing one of the treated products (McAuley et al. 2015). 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, seller of the product, etc. Table 2 contains summary statistics that describe the main variables of our empirical model presented in the next section.

**Table 2: Descriptive Statistics**

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Log(Sales rank) | 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 |
| Log(Number of reviews) | 13,680,370 | 3.04 | 2.39 | 0 | 9.95 |
| Log(Price) | 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 |

## 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 below, but we first describe our primary identification strategy. Our main identification scheme relies on panel data and a difference-in-differences methodology to measure the causal effect of IoT by contrasting over time the outcomes of the products that received the treatment with that of a control group that did not receive the treatment. Our main estimating equation for product $i$ in market (i.e., country) $c$ and time period (i.e., day) $t$ is:

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

where $s_{ict}$ is the sales rank of the 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, $\beta^{T}$, captures the effect of 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. We also include linear and non-linear time trends for each market, $\boldsymbol{\tau}_{ct}$, and product-market-level fixed effects, $\boldsymbol{a}_{ic}$, controlling for observed and unobserved heterogeneity. Finally, $\varepsilon_{ict}$ is an error term. We also examine several alternative econometric specifications as robustness checks.

Following the extant literature, sales rank for each product is used as a proxy for demand based on prior research (e.g., (Archak et al. 2011; Brynjolfsson et al. 2003; Carmi et al. 2017; Chen et al. 2008; Chevalier and Goolsbee 2003; Ghose and Sundararajan 2006; Gu et al. 2012)). 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., (Adamopoulos and Tuzhilin 2015; Archak et al. 2011; Chevalier and Mayzlin 2006)).

The aforementioned identification strategy enables us to overcome several potential endogeneity challenges. Apart from employing panel data and the difference-in-differences 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) due to the experimental nature of the introduction of the IoT technology. Beyond the utilized quasi-experiment and the panel structure of our dataset with variation both with-in treated products in the same country and with-in treated products across markets, we also tap into similar (non-treated) control products. More specifically, we utilize as controls similar non-treated substitute products as these products are perceived as similar and comparable choice alternatives by the consumers.

Such controls are based on the products that belong to the same product category and consumers frequently view online when viewing one of the treated products (McAuley et al. 2015). In addition, we utilize as controls the same products in different markets where they are not treated at all (e.g., Canada); this eliminates any potential differences among treated and non-treated control products. Finally, we conduct an extensive set of robustness checks and falsification tests to further enhance our empirical analyses.

## Main Results

In the following paragraphs, we discuss the estimation results of our empirical model examining the impact of the IoT sales channel on product sales. Table 3 provides estimates of our main model specifications. In particular, Model (1) examines the impact of IoT adoption on the sales of the products while accounting for the product rating, (log of) the total number of user-generated reviews and non-linear time trends, (log of) the price of the product and the product seller as well as product-market fixed effects. 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 3, we find that the coefficient of the IoT channel adoption variable is negative and statistically significant, suggesting that when a product is becoming eligible for IoT purchases, the product's sales increase (i.e., lower sales rank). Apart from being statistically significant at the 0.1% level, this effect is also economically significant as the adoption of the IoT technology leads to an improvement of about 13.28% in sales ranking (i.e., $100 * (e^{-0.1425} - 1)$ ). 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 on 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 0.54%. 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. The estimated coefficient is also in compliance with prior literature (e.g., (Chen et al. 2004; Dhanasobhon et al. 2007; 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 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 2.45% (i.e., $100 * (e^{-0.0248} - 1)$). Evaluating the rest of the variables in Table 3, we notice that the volume of reviews has a positive effect on product sales as well (Adamopoulos and Tuzhilin 2015). In particular, if the number of reviews is increased by 1%, the sales rank improves by about 0.42%. 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 0.71% (i.e., $0.01 * 100 * (e^{0.5380} - 1)$).

**Table 3: IoT Effect - Fixed-effects Models**

| | 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 trend (non-linear) | Yes | Yes | Yes |
| Additional controls | No | No | Yes |
| R-squared | 0.2545 | 0.2563 | 0.2563 |
| N. of observations | 13,680,370 | 13,680,370 | 13,680,370 |

Notes: Panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

Focusing on the emerging IoT technologies, our paper is the first to study the effect of the adoption of the IoT as a sales channel and demonstrate that such a technology adoption enhances the sales of products. While the extant literature that has examined the effect of the adoption of other sales channel has provided conflicting evidence, our paper reveals that the adoption of IoT in particular as a sales channel increases the product sales; the effect is statistically and economically significant and survives an extensive set of robustness and falsification tests. These findings highlight the business value of the IoT technology for retailers and brands while they offer timely implications for firms and future research.

### *Heterogeneity of IoT Effects*

In order to leverage the Internet of Things as a sales channel, businesses and practitioners will need to develop sufficient knowledge to make such technology investments. In this section, we also delve into the differences in the impact of the IoT channel adoption and we explore the effect of heterogeneity by examining important moderating effects of the IoT channel on sales growth providing greater insights into the effectiveness of IoT technologies.

We first examine the moderating effect of price on the effect of the adoption 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 worthwhile examining whether product price moderates the effectiveness of the IoT channel on sales growth. Table 4 examines the moderating effect of price on the effect of the adoption of the IoT channel on product sales. Based on these results, we find a positive and significant moderating effect of 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 the 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.

**Table 4: Heterogeneity of IoT Effect – Product Price**

| | 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) x 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 trend (non-linear) | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2545 | | 0.2563 | | 0.2563 | |
| N. of observations | 13,680,370 | | 13,680,370 | | 13,680,370 | |

Notes: Panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

Moreover, the second moderating effect we study is the product classification of search and experience goods. The experience versus search goods classification (Nelson 1970, Nelson 1974) provides important insights into how consumers' search and purchase behaviors differ for search and experience goods. Based on this classification, consumers can readily observe the quality of search goods prior to purchase whereas they can only determine the quality of experience goods after consuming or experiencing them. One might expect that the IoT channel effectiveness on driving sales growth varies for search versus experience goods and it remains an empirical question which product class is more likely to benefit more from the adoption of such IoT technologies. Based on the results presents in Table 5, we find a positive and significant moderating effect of the search -versus experience- classification suggesting that the adoption of IoT technologies as a sales channel is more effective for experience goods. This interesting finding that experience goods, rather than search ones, are benefiting more from the adoption of the IoT channel is in accordance with the observation that experience goods typically have lower price elasticity than search goods and might create inertia for consumers (Nelson 1970). Besides, this finding is in compliance with research that has demonstrated consumers face higher information search and switching costs –both cognitive and physical costs– when evaluating experience goods, rather than search ones, (Huang et al. 2009) and, thus, they tend to be more loyal to experience goods (Bharadwaj et al. 1993). This finding unveils important managerial implications for online retailers with regards to how they can strategically leverage IoT technologies since experience goods have traditionally posed a major challenge for online retailers.

**Table 5: Heterogeneity of IoT Effect – Search versus Experience Goods**

| | **Model 1** | **Model 2** | **Model 3** |
|---|---|---|---|
| Rating | -0.0236 ***<br>(0.0041) | -0.0248 ***<br>(0.0041) | -0.0248 ***<br>(0.0040) |
| Number of reviews (log) | -0.4096 ***<br>(0.0099) | -0.4169 ***<br>(0.0101) | -0.4174 ***<br>(0.0101) |
| Price (log) | 0.5428 ***<br>(0.0205) | 0.5421 ***<br>(0.0205) | 0.5420 ***<br>(0.0205) |
| Treatment (IoT eligible) | -0.1501 ***<br>(0.0074) | -0.1494 ***<br>(0.0074) | -0.1498 ***<br>(0.0074) |
| Treatment (IoT eligible) x Search good | 0.0740 ***<br>(0.0221) | 0.0747 ***<br>(0.0221) | 0.0740 ***<br>(0.0221) |
| Fraction of solicited reviews | | 0.5376 ***<br>(0.0781) | 0.5383 ***<br>(0.0781) |
| Constant | 9.0891 ***<br>(0.0647) | 9.0985 ***<br>(0.0647) | 9.1005 ***<br>(0.0647) |
| Product-market fixed effects | Yes | Yes | Yes |
| Additional product controls | Yes | Yes | Yes |
| Time trend (non-linear) | Yes | Yes | Yes |
| Additional controls | No | No | Yes |
| R-squared | 0.2545 | 0.2563 | 0.2563 |
| N. of observations | 13,680,370 | 13,680,370 | 13,680,370 |

Notes: Panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

### *Robustness Checks*

In this section, we undertake an extensive set of tests to assess the robustness of the main results and further strengthen our findings by eliminating competing explanations.

First, we replicate the analysis including year-month fixed effects (see Table 6) allowing for alternative non-linear trends that could potentially bias the results while capturing additional seasonality effects. As shown in Table 6, the results corroborate our findings.

**Table 6: IoT Effect - Fixed-effects Models with Additional Year-Month Fixed-effects**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | -0.0236 | *** | -0.0248 | *** | -0.0248 | *** |
| | (0.0041) | | (0.0040) | | (0.0040) | |
| Number of reviews (log) | -0.4155 | *** | -0.4231 | *** | -0.4230 | *** |
| | (0.0100) | | (0.0101) | | (0.0101) | |
| Price (log) | 0.5428 | *** | 0.5421 | *** | 0.5421 | *** |
| | (0.0205) | | (0.0204) | | (0.0205) | |
| Treatment (IoT eligible) | -0.1469 | *** | -0.1463 | *** | -0.1464 | *** |
| | (0.0071) | | (0.0071) | | (0.0071) | |
| Fraction of solicited reviews | | | 0.5453 | *** | 0.5453 | *** |
| | | | (0.0782) | | (0.0782) | |
| Constant | 9.0846 | *** | 9.0950 | *** | 9.0945 | *** |
| | (0.0644) | | (0.0644) | | (0.0644) | |
| Product-market fixed effects | Yes | | Yes | | Yes | |
| Additional product controls | Yes | | Yes | | Yes | |
| Year-Month fixed effects | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2557 | | 0.2574 | | 0.2574 | |
| N. of observations | 13,680,370 | | 13,680,370 | | 13,680,370 | |

Notes: Panel data analysis with product-market fixed effects and month-year fixed effects. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Then, we repeat the analysis including only observations with a product price less than or equal to $100 in order to examine the robustness of the results to outliers in terms of product price (see Table 7); the product price in this set of 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) due to the limited price range here. As shown in Table 7, the results remain robust; the results are also robust to any variable transformation in our model.

**Table 7: IoT Effect – Fixed-effects Models for Products with a Maximum Price of $100**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | -0.0249 | *** | -0.0262 | *** | -0.0261 | *** |
| | (0.0041) | | (0.0041) | | (0.0041) | |
| Number of reviews (log) | -0.4119 | *** | -0.4192 | *** | -0.4197 | *** |
| | (0.0101) | | (0.0101) | | (0.0101) | |
| Price | 0.0281 | *** | 0.0281 | *** | 0.0281 | *** |
| | (0.0007) | | (0.0007) | | (0.0007) | |
| Treatment (IoT eligible) | -0.1434 | *** | -0.1426 | *** | -0.1431 | *** |
| | (0.0070) | | (0.0070) | | (0.0070) | |
| Fraction of solicited reviews | | | 0.5343 | *** | 0.5350 | *** |
| | | | (0.0782) | | (0.0782) | |
| Constant | 10.0164 | *** | 10.0244 | *** | 10.0264 | *** |
| | (0.0268) | | (0.0268) | | (0.0268) | |

| | | | |
|---|---|---|---|
| Product-market fixed effects | Yes | Yes | Yes |
| Additional product controls | Yes | Yes | Yes |
| Time trend (non-linear) | Yes | Yes | Yes |
| Additional controls | No | No | Yes |
| R-squared | 0.2453 | 0.2470 | 0.2471 |
| N. of observations | 13,475,494 | 13,475,494 | 13,475,494 |

Notes: Panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products, excluding observations with product price larger than $100. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product. The price variable is not log-transformed. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

Furthermore, one might be concerned that the results regarding the effectiveness of the IoT channel in increasing product sales might be driven by potential confounds, such as word-of-mouth and buzz around IoT technologies. We evaluate this possibility by capturing the effect of market-specific web search trends regarding IoT using data from Google Trends (see Table 8) (Adamopoulos and Todri 2014; Adamopoulos and Todri 2015a; Archak et al. 2011). As shown in Table 8, all the results remain highly robust. Based on the results, the web search trends capture a small portion of the previously identified IoT effect as the estimated effect only decreased from 13.28% to 12.92% and the fit of our model specifications is further increased; however, as we see the IoT effect is not driven by just the buzz around IoT.

**Table 8: IoT Effect - Fixed-effects Models with IoT-related Web Search Trends**

| | **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) | |
| 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 trend (non-linear) | Yes | | Yes | | Yes | |
| Web search trends | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2616 | | 0.2639 | | 0.2646 | |
| N. of observations | 13,680,364 | | 13,680,364 | | 13,680,364 | |

Notes: Panel data analysis with product-market fixed effects, non-linear time trend, and IoT-related web search trends. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

In addition, even though we have employed an advanced identification strategy that rules out alternative explanations, in order to alleviate any remaining endogeneity concerns we conduct the analysis again excluding observations for products that were treated in more than one market (see Table 9) as these products could have potentially been strategically selected by the retailer. As shown in Table 9, all the results further corroborate our main findings, alleviating any potentially remaining endogeneity concerns.

**Table 9: IoT Effect - Fixed-effects Models Excluding Potentially Endogenous Observations**

| | 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 fixed effects | Yes | | Yes | | Yes | |
| Additional product controls | Yes | | Yes | | Yes | |
| Time trend (non-linear) | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2592 | | 0.2609 | | 0.2610 | |
| N. of observations | 13,347,445 | | 13,347,445 | | 13,347,445 | |

Notes: Panel data analysis with product-market fixed effects and non-linear time trend 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 they were treated, these products in other markets (non-treated at any time in these markets), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

## Falsification Tests

One might think that it is possible that the previous set of models are simply picking up spurious effects as a result of pure coincidence, a general increase in the corresponding metrics, or other unobserved factors. To assess the possibility that the aforementioned findings are a statistical artifact and the identified positive significant effects were captured by chance or because of other confounding factors, we run various falsification tests ("placebo" studies) using the same models as above (in order to maintain consistency) but randomly indicating: i) which products were eligible for purchase via the IoT channel (i.e., random product), ii) when they became eligible (i.e., random time period), and iii) where they became eligible (i.e., random market). The results of these falsification tests are shown in Tables 10-12. Specifically, Table 10 shows the results of the falsification test randomly indicating which products were treated (i.e., random product); Table 11 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 12 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). 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 our specifications and further validating that we have indeed estimated the actual demand effects of the Internet of Things sales channel.

**Table 10: Falsification Test (Pseudo-Treatment – Random IoT-eligible Product)**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | -0.0227 | *** | -0.0240 | *** | -0.0239 | *** |
| | (0.0041) | | (0.0041) | | (0.0041) | |
| Number of reviews (log) | -0.4123 | *** | -0.4197 | *** | -0.4202 | *** |
| | (0.0099) | | (0.0101) | | (0.0101) | |
| Price (log) | 0.5444 | *** | 0.5437 | *** | 0.5436 | *** |
| | (0.0205) | | (0.0205) | | (0.0205) | |
| Pseudo-Treatment (Pseudo product) | -0.0127 | | -0.0130 | | -0.0136 | |
| | (0.0112) | | (0.0112) | | (0.0112) | |

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Fraction of solicited reviews | | | 0.5425 | *** | 0.5431 | *** |
| | | | (0.0782) | | (0.0782) | |
| Constant | 9.0909 | *** | 9.1004 | *** | 9.1024 | *** |
| | (0.0648) | | (0.0647) | | (0.0647) | |
| Product-market fixed effects | Yes | | Yes | | Yes | |
| Additional product controls | Yes | | Yes | | Yes | |
| Time trend (non-linear) | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2540 | | 0.2557 | | 0.2557 | |
| N. of observations | 13,680,370 | | 13,680,370 | | 13,680,370 | |

Notes: Falsification test based on panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. The pseudo-treatment variable randomly indicates which products were treated in which market and what time period (i.e., random IoT eligible product). 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

**Table 11: Falsification Test (Pseudo-Treatment – Random Market)**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | -0.0227 | *** | -0.0240 | *** | -0.0239 | *** |
| | (0.0041) | | (0.0041) | | (0.0041) | |
| Number of reviews (log) | -0.4124 | *** | -0.4198 | *** | -0.4202 | *** |
| | (0.0099) | | (0.0101) | | (0.0101) | |
| Price (log) | 0.5444 | *** | 0.5436 | *** | 0.5436 | *** |
| | (0.0205) | | (0.0205) | | (0.0205) | |
| Pseudo-Treatment (Pseudo market) | -0.0012 | | -0.0005 | | -0.0005 | |
| | (0.0123) | | (0.0123) | | (0.0123) | |
| Fraction of solicited reviews | | | 0.5424 | *** | 0.5430 | *** |
| | | | (0.0782) | | (0.0782) | |
| Constant | 9.0909 | *** | 9.1003 | *** | 9.1023 | *** |
| | (0.0648) | | (0.0647) | | (0.0647) | |
| Product-market fixed effects | Yes | | Yes | | Yes | |
| Additional product controls | Yes | | Yes | | Yes | |
| Time trend (non-linear) | Yes | | Yes | | Yes | |
| Additional controls | No | | No | | Yes | |
| R-squared | 0.2540 | | 0.2557 | | 0.2557 | |
| N. of observations | 13,680,370 | | 13,680,370 | | 13,680,370 | |

Notes: Falsification test based on panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. The pseudo-treatment variable randomly indicates for treated products and the time period they were treated in which market they were treated (i.e., random market). 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

**Table 12: Falsification Test (Pseudo-Treatment – Random Time Period)**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | -0.0227 | *** | -0.0240 | *** | -0.0239 | *** |
| | (0.0041) | | (0.0041) | | (0.0041) | |
| Number of reviews (log) | -0.4124 | *** | -0.4198 | *** | -0.4202 | *** |
| | (0.0099) | | (0.0101) | | (0.0101) | |
| Price (log) | 0.5444 | *** | 0.5436 | *** | 0.5436 | *** |
| | (0.0205) | | (0.0205) | | (0.0205) | |

| | | | |
|---|---|---|---|
| Pseudo-Treatment (Pseudo time) | 0.0063<br>(0.0087) | 0.0060<br>(0.0087) | 0.0062<br>(0.0087) |
| Fraction of solicited reviews | | 0.5423 ***<br>(0.0782) | 0.5429 ***<br>(0.0782) |
| Constant | 9.0908 ***<br>(0.0648) | 9.1003 ***<br>(0.0647) | 9.1022 ***<br>(0.0647) |
| Product-market fixed effects | Yes | Yes | Yes |
| Additional product controls | Yes | Yes | Yes |
| Time trend (non-linear) | Yes | Yes | Yes |
| Additional controls | No | No | Yes |
| R-squared | 0.2539 | 0.2557 | 0.2557 |
| N. of observations | 13,680,370 | 13,680,370 | 13,680,370 |

Notes: Falsification test based on panel data analysis with product-market fixed effects and non-linear time trend. The estimation sample includes observations about treated products before and after the treatment in the market they were treated, these products in other markets (either non-treated or treated at the same or different time), and non-treated products in the same market that are similar to treated products. Negative coefficients correspond to increase in sales (i.e., lower sales rank). The number of reviews variable corresponds to the log of the number of user-generated reviews for each product and the price variable corresponds to the log of the price for each product. The pseudo-treatment variable randomly indicates for treated products in the market they were treated what time period they were treated (i.e., random time period). 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. Significance levels: * p<0.05, ** p<0.01, *** p<0.001

## Discussion and Managerial Implications

The "Internet of Things" (IoT) is rapidly becoming one of the most popular emerging technologies in business and society. Given the unpreceded opportunities IoT generates for brands and retailers, it is important to generate timely insights regarding the business value of IoT and understand whether the introduction of an IoT technology into the available purchase channels for consumers affects the sales of products. In this study, using empirical data from an online retailer who adopted an IoT sales channel and utilizing a quasi-experimental research design, we examine the effect of the adoption of the IoT technology on product sales and demonstrate the business value of IoT for retailers and brands. Besides, we also delve into the effect heterogeneity and examine important moderating effects on the impact of IoT. All the findings of the conducted econometric analyses are highly robust and have survived a wide range of robustness checks and falsification tests. To the best of our knowledge, this is the first paper to study the impact of an IoT technology on product sales.

The findings of this study have also important managerial implications. For instance, we find based on the results that IoT technologies have a positive effect on sales growth. This effect is both statistically and economically significant. In addition, it is an important and timely finding for managers as we are still in the early stages of development and deployment of IoT technologies. For instance, such knowledge of the effect of the IoT sales channel is important for determining the attractiveness of investment in IoT technologies in retail. Our findings contribute towards this as they clearly show the potential of such IoT investments and suggest that retailers and marketers should further 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 additional insights into consumer behavior and a more detailed understanding of the heterogeneity of the effectiveness of adoption of IoT technologies in the retail industry. Such moderating effects are important for managers as they provide actionable insights and help businesses further understand which products would accrue the highest benefit from such technological innovations and which would benefit the least (Todri and Adamopoulos 2014). Therefore, the results of this study showcase to 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 (Klein 1998; Nelson 1970). In addition, these findings can contribute to more accurate product sales predictions for retailers leading to more efficient supply chain operations and more advanced business analytics (Adamopoulos et al. 2018; Ghose et al. 2017; Ghose and Todri-Adamopoulos 2016).

Beyond the aforementioned managerial implications, the examined IoT channel and the corresponding findings of this study can inform several managerial decisions and practices regarding future embodiments of IoT technologies. More specifically, the examined IoT technology 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 rather than just purchase analytics and better address the evolving needs of consumers while exploiting additional revenue opportunities through novel add-on services (Adamopoulos 2013; Adamopoulos and Todri 2015b; Adamopoulos and Tuzhilin 2014). In particular, the information of 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).

Future research can examine additional moderating effects on the relationship of IoT channel adoption and sales growth to further enrich our understanding regarding the impact of IoT technologies on retailing and further describe the underlying mechanism. For instance, future research can examine the moderating effect of alternative product attributes and classifications on the effectiveness of the IoT sales channel. In addition, future research can examine whether the identified increase in product sales is mainly because of increased demand levels from the existing customer base of the retailer marketplace or mainly due to new consumers (Adamopoulos and Todri 2014; Adamopoulos and Todri 2015a). Moreover, future research can examine the business value of IoT technologies in other industries and verticals beyond retailing.

While this paper takes important steps towards studying the business value 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 marketplace. Another limitation of our data set is that some of the products are not available in all markets. Our dataset is also limited to aggregate daily data and not at a more granular level. Despite these limitations, our contribution may 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.

## Conclusions

Using empirical data from a multi-national online retailer that introduced an IoT sales channel and utilizing 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 Internet of Things for retailers and brands. Our analyses reveal a statistically and economically significant increase in sales due to the introduction of the IoT technology as a direct sales channel. Besides, we conduct additional analyses of the IoT effect and also delve into the effect heterogeneity examining important moderating effects on the impact of the IoT channel. Our findings reveal that less expensive products as well as experience –versus search– goods accrue the highest benefits leveraging more effectively the novel IoT channel. We also conduct an extensive set of robustness checks and falsification tests to further validate our analyses. 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 and the corresponding demand effects drawing significant implications for managers and future research directions.

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