A MULTI-SCREEN STRATEGY FOR SELLING MOBILE CONTENT TO CUSTOMERS

Completed Research Paper

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Abstract

Our research aims to discover the role of multiple smart devices and their different screen sizes in paid content sales, thus building a multi-screen content sales strategy. Our econometric model adopts a difference-in-differences method to measure the impact of multi-screen devices on users' content consumption through screen size effects. In a natural experiment setting, we sample 238 individual customers who registered a single smartphone with a 3- to 4-inch screen at the beginning and then added devices with a similar or larger screen. Our paper determines the parameters in existing theoretical frameworks of online consumer utility (product selection and digital content price) to determine paid content purchase behavior in a multi-screen environment. Our key findings are that the price sensitivity of content decreases as a user registers new smart devices and registering new devices with larger screens positively influences less popular content consumption more than a small screen device does.

Keywords: multi-screen, mobile device, mobile content, econometric analyses, digital business model

Introduction

If there's going to be a third category device, it's going to be better at browsing the web, reading ebooks than a laptop and smartphone, otherwise it has no reason for being.

—Steve Jobs, chairman and CEO, Apple, iPad Keynote 2010

As revolutionary mobile (and smart) devices capable of wireless Internet service have been introduced, the number of different screens equipped with identical functionalities that people confront has been increasing (Reeves et al. 1999). Such a breakthrough technology consequently offers a wide variety of sales channels to mobile content providers. Mobile content providers utilize a multi-screen strategy, or N-screen strategy, providing the same content across a variety of platforms (e.g., tablet PCs and smart phones), so that multiple mobile devices can share and consume seamlessly. For example, Amazon.com's users can access ebooks purchased from the company's online store on up to six devices (Kindles, iPhones, iPads, etc.).

However, as noted in the opening quote, a device with a different physical form is developed to differentiate itself from others even if it is equipped with identical functionalities (Chae and Kim 2004). The success of smart devices with variety of screen sizes obviously relies on users' different collaborative and social interactive benefits, depending on the size of the display (Dudfield et al. 2001), though these devices all have technically equal capabilities. Bradley et al. (1992) also find that different screen sizes elicit different levels of user arousal and subsequent behavior, where the purchase of paid content or the consumption of free content can be affected by different levels of excitability. Our research is inspired from previous studies that question whether certain types of content can interact with screen size to increase various effects (Reeves et al. 1999). Smart device owners may seem to purchase or consume mobile content such as ebooks, music, and video indifferently; however, extensive works in psychology and media indicate that online users with different screen size devices have different content preferences. Therefore understanding the different content consumption behaviors of users with both small and large screen devices is important for the success of a multi-screen strategy.

Our research questions are intuitive: Does a multi-screen strategy truly differentiate between different screen size devices and stimulate content providers to offer a variety of digital products? If not, is a multi-screen strategy an oversimplified content service that ignores the characteristics of devices, including screen size? With these issues in mind, our research aims to determine the role of different screen size devices in paid content sales from a business intelligence perspective, considering content profile information such as size, content price, and content sales performance. To our knowledge, our study is the first attempt at building a research model to demonstrate consumers' decision making in purchasing mobile content as the number of devices of different screen sizes a user owns increases. It is also the first to provide empirical data supporting existing online consumer purchase behavior theories. We propose business strategies for mobile content providers to identify the types of devices users own and to offer appropriate paid content. Varian (1998) defines paid content as a special form of information good that provides content providers with revenue from customers, business growth, and steady future investment. Stahl and Maass (2006) define paid content as the non-free sales and distribution of an information-based content product. The need for such business strategies is apparent: For example, in the ebook market, a biography of Steve Jobs over 400 pages long is being highly recommended to users who own only a 3- to 4-inch smartphone.

Using the monthly sales data of one of the biggest ebook retailers in Korea from January 2011 to December 2011, we show that user content purchase behavior changes as the number of different screen size devices owned increases, starting with a small screen device. To create a natural experimental data set, we sample 238 users who registered a single smartphone (iPhone or Android phone) at the beginning of their service and added one or more devices with similar or larger screen sizes within our sample time period in the natural experiment setting. In particular, we examine how adding a large screen tablet PC, such as an iPad or Android Tab, changes the types of mobile content bought, which we compare to the type of product bought by users who add only similar screen size devices, such as an iPhone or Android Phone. Our method controls for differences in consumer preference across devices through screen size effects. Thus we use the addition of new devices with small or large screens by users to identify the effects of improved mobile content options, such as price, on online choice, using a difference-in-differences strategy. eBooks are a good example for demonstrating the difference in user content preferences from that determined in previous user online reading behavior studies. By focusing on ebooks, we can study mobile content, an information product, where brand- and product-specific factors are hampered or prevented from having unintended effects such as product or consumer substitution (Lal and Sarvary 1999). We believe that ebooks have similar advantages of easily identifiable, dominant content retailers, as Forman et al. (2009) describe in a product purchasing behavior study with book data.

Data analysis shows that the variety of screen types directly increases the likelihood of purchasing paid content online since consumers with both small and large screen devices achieve better usability than users with only small screens (Smith and Telang 2009) and consequently have a higher probability of purchasing paid content. First, different purchase behavior depending on content popularity is observed in a multi-screen environment. In fact, screen size turns out to be a critical determinant of users' psychological responses (Reeve et al. 1999) and determines better purchase performance for content in niche categories, which often require higher search costs than content in the best-selling category. Second, we find that content price sensitivity is mitigated as users register new smart devices and, more significantly, if a newly added device is a large screen device.

The remainder of this paper proceeds as follows. The next section reviews the relevant literature pertaining to the impact of device screen size on content usage and purchase behavior and derives hypotheses from previous research. The third section describes the data used for this study. The fourth section presents our main econometric model and briefly discusses the theoretical basis for each hypothesis. The paper then discusses our data and presents our research models and results. Finally, it discusses the implications of our findings, the limitations of our analysis, and areas for future research.

Related Works

This paper focuses on determining how adding a larger screen affects the increase in consumption of paid content as the number of screen sizes increases. In other words, we aim to understand the factors behind a successful multi-screen strategy having a synergistic effect and raising content sales. Just as Forman et al. (2009) select factors determining purchase behavior differences in a traditional multichannel environment from product properties such as popularity (convenience and product selection) and price, we derive our hypotheses to measure the impact of different content consumption behavior on a multi-screen environment from content information such as popularity (product selection) and price.

Search Cost and Product Selection

Our first hypothesis involves the impact of screen size variety on purchasing digital content from a popularity perspective. We label content listed as top sellers or likely to be recommended to online consumers as popular. The popularity of content in a multi-screen world, however, can be represented by a top download rank and having a higher probability of being recommended to users (Smith and Telang 2009). Forman et al. (2009) emphasize that product selection is an important factor in purchase behavior in a multi-screen environment. In addition, popularity in a multi-screen environment substantially eliminates search costs and raises customer utility because a user has to expend considerable effort if the content he or she is willing to buy must be searched for on a limited display size (Donio et al. 2006). In other words, different consumer responses and purchase behaviors can be clearly observed because top sales or highly recommended content mitigates or even eliminates search costs for both users with small screen devices only and users with various screen size devices.

According to Balasubramanian (1998), consumers are fully informed about the content information and both users with small screens only and those with small and large screens face equal or no search costs. This setting is similar to the market for popular content, which can be easily found without wasting efforts to search for it. Consumers are less likely to find less popular content on the top-ranked list or being recommended. This can be interpreted as an increase in average search costs and a decrease in user utility for given content. According to Cheng et al. (2007), ethnic books in the United States are an example of such a market.

In this setting, a variety of screen sizes has a greater effect on the likelihood on purchasing content since device screen size severely impacts the user's ability to access information (Albers et al. 2002. In addition, several human–computer interaction (HCI) studies highlight problems with search interfaces for small screen devices (Sweeney and Crestani 2006). Specifically, Jones et al. (1999) show that a small screen increases user interaction efforts and reading time. In other words, navigating through information with limited screen space essentially increases search costs. Mahmood et al. (2000) note that high search costs often discourage users from discovering new or unfamiliar products, leading to passive product purchasing due to narrow product choice. According to Rothschild (1974), rational customers continuously weigh expected benefits against search costs and search for products only if the expected benefit is greater than the search cost. Therefore expected search cost is greater for users who own only small screen devices, leading to low purchase rates for less popular content. Users who own a variety of screen sizes, however, take advantage of larger screens to lower search costs and raise their chances of discovering new or unfamiliar products and demonstrate better and unique (closer to the "true" content preference of users) purchase performance.

Brynjolfsson et al. (2011) find that search cost is an important indicator associated with the increased sales of niche products (content). With a vast variety of content on the multi-screen market, devices offering lower search costs allow users to acquire product information with greater convenience and lead to increased demand for unpopular content categorized as niche products. A variety of screen sizes helps the multi-screen market shift the balance from limited best-selling content to niche content (Brynjolfsson et al. 2011); on the other hand, a small screen device narrows the concentration of popular content sales.

Acquiring multiple smart devices increases the needs of contents to consume and the amount of time they spend on digital content and consequently improves the sales performance of both popular and less popular digital content. Nevertheless, our Hypotheses 1A and 1B focus on the positive influence on sales performance of less popular content due to increased content accessibility in a multi-screen environment.

Hypothesis 1A (product selection): Purchases of less popular digital content increase as the number of screens increases.

Hypothesis 1B (product selection): Purchases of less popular digital content increase more from the addition of large screen devices than from the addition of small screen devices.

For instance, consider an ebook that is not likely to be recommended and not listed as a top seller at Amazon.com. As soon as a user visits Amazon.com, he or she must search for an ebook and confirm information to buy it. If the user owns only a small screen device, the limited display format will force the user to expend efforts continuously zooming in and out and navigating through a complex mobile interface version. Hypotheses 1A and 1B imply that the effect of screen size variety on the sales of ebooks less likely to be recommended is larger than the effect on top sellers. We take into account the fact that not all kinds of content are listed as top sellers or recommended to eliminate the search cost.

Content Price

Content price is a key element in a digital content provider's commercial success (Brynjolfsson et al. 2011). Our second hypothesis is designed to determine how the price of content affects customer purchase behavior by examining the role of content price and the variety of screen sizes in a multi-screen environment. Rangaswamy and Gupta (2000) argue that consumer decisions and purchase behavior for new products and technologies is significantly influenced by the digital medium, such as smart devices in a multi-screen environment. Lang et al. (1997) empirically show that content on a larger screen size stimulates greater arousal than content displayed on a smaller scale and, as a result, engages the appetitive or aversive motivation to purchase it.

Previous marketing research shows that digital product market price sensitivity decreases when quality information is provided (Bakos 1997). In fact, price sensitivity decreases if the market decreases search costs for quality information regarding digital content (Bakos 1997). Since the main potential advantage of having a large screen device is a reduction in search costs for product and product-related information, lowering the search cost for quality information reduces price sensitivity (Degeratu et al. 1998). Lynch and Ariely (2000) also indicate that easier quality information searches outweigh content price, so that a large screen with a better search environment increases paid content sales performance.

We focus on how a variety of screen sizes represents user utility and how satisfaction with previous content experiences is associated with changes in price sensitivity. As previous studies indicate, greater screen size diversity raises user satisfaction and the utility of consuming quality digital content. According to Varian (1998), digital content is categorized as an experience good with economies of scale. The major characteristic of an experience good is that users must experience the product before they can know what it is. Brynjolfsson et al. (2011) note that the price of digital content offers a better user experience. Since the quality of an experience good is directly influenced by consumer utility (satisfaction from previous experiences) and vice versa (Stahl and Maass 2006), the variety of screen sizes increases the need for better user experience from paid content and offers interactive elements that can be seamlessly integrated with the content (Brynjolfsson et al. 2011), with users becoming less sensitive to content prices. Therefore the impact of content price is tempered by the increased expectation of better user experiences from the variety of screen sizes.

Hypothesis 2A (price): Digital content price sensitivity decreases as the number of screen devices increases.

Hypothesis 2B (price): Digital content price sensitivity decreases more from the addition of larger screen devices than from the addition of smaller screen devices.

Data Description

To examine how content consumption behavior varies with the variety of screen sizes users own, we require detailed data regarding how online consumer purchases vary across consumer status changes by adding more smart devices. We use ebook purchase data from one of the biggest ebook sellers in Korea. This is an especially good setting for testing our hypothesis for a number of reasons. First, ebooks represent commodity content wherein brand- and product-specific factors are less likely to influence content consumption behavior (Forman et al. 2009) across smart devices. In fact, the study of the ebook market itself is economically large. The International Publishers Association stated that the worldwide ebook market was $3.9 billion in 2010, with over 64% yearly growth, and is expected to reach $75.8 billion in 2013. Second, as Davenport and Beck (2001) appreciate, ebooks are a perfect target for research at the very beginning of the paid content market, which is nurtured by high search costs and heterogeneous quality levels for high-quality paid content markets for particular needs and on particular topics. Third, ebooks are an inexpensive "commodity" information product. They represent a wide variety of other commodity digital content types available in a multi-screen environment, including images, video clips, and entertainment content. Finally, Forman et al. (2009) note that ebook retailers, like offline book retailers, are easy to identify. In other words, our data are a good sample covering the overall ebook market and we can set up an effective natural experiment to precisely explore different content consumption behaviors in a multi-screen environment.

Our collected data cover individuals' activity and content purchase history over 12 months. Since a small number of ebook solution providers dominate the entire Korean ebook market, our data represent the ebook content consumption of Korean consumers in a multi-screen environment. In addition, analysis of Korean user digital consumption behavior data is especially important because the market behavior in Korea is a good reference for the US market and even globally, despite cultural differences in the adoption of smart devices and digital content. May et al. (2011) forecasts greater relative growth of content and the smart device market from 2010 to 2013 in Asian markets, although the US ebook market is experiencing faster growth than the other regions: 76.2% growth of the US smart pad or tablet PC market and 300% growth of the Korean market in 2010. The Korean Census Bureau reports that 2 million smart pads have been sold and that smart pad users are expected to number over 5 million by 2013. Greater populations of smartphones users in both the US and Korea will own tablet PCs or large screen smart devices sooner than later.

Our collected data consist of ebook information—such as the publisher, author(s), length of description, and publication date—and user information—such as the number of devices owned, types of devices, general demographic profile (age, gender, subscription date, and number of days since the subscription date), and monthly ebook purchase history. We collect data for the period from January 2011 to December 2011. Forman et al. (2009) note that 12 months of data is an adequate range for time series to separate short-run, curiosity effects from given experimental stimuli and determine the long-run effects of new devices greater than three months. Stahl and Maass (2006) show the critical importance of study duration by demonstrating different responses from short- and long-run effects. The descriptive statistics of our data are provided in Table 1 and the next section describes the construction of critical variables.

From the collected dataset, we select 238 users via random sampling. Users in the treatment group initially owned a screen device (smart phone) and then registered a larger screen device as a second device. Users in the control group also owned a small screen device as their first device; however, they registered similar or equally small screen devices as second devices. The time gap between registering the first and second devices of both the treatment and control group users is at least three months to eliminate possible bias and capture changes in content usage and purchase behavior due to larger screen device registration.

In addition, since our dataset does not directly contain individual user income profiles due to privacy issues, we adopt an alternative approach to overcome possible bias from an income effect. First, the control and treatment groups are selected according to the matched sample design to minimize the possibility in differences of user profile variables such as age, gender, and day since registered between the two groups. Second, we select users who eventually owned two smart devices equally in the natural experiment; all users in both groups initially owned a smart phone equipped with a small screen. Users may have added different screen size devices as second devices as a matter of fact the screen size does not create the price difference purchasing smart devices. Both small and large screen devices are sold for similar prices ranges. Therefore, both groups of users eventually spent equal or similar amounts to purchase their second devices, which allow us to successfully mitigate possible income bias from experiment settings and to select users with similar income levels. The summary statistics in Table 1 show the results of random and balanced samplings from the collected dataset. A total of 238 sampled users fit such requirements.

Table 1. A Sample Table

Variable	Observations	Mean	Std. Dev	Min	Max
User content purchase data					
PurchaseYN (1 purchased, 0 not)	192,529	0.0425	0.2017	0	1
NewDeviceReg (1 registered, 0 not)	192,529	0.1899	0.3922	0	1
WiderDeviceReg (1 registered, 0 not)	192,529	0.0702	0.2555	0	1
Very Popular Content (rank 1–50)	192,529	0.1869	0.1354	0	1
Popular Content (rank 51–250)	192,529	0.0508	0.2197	0	1
Less Popular Content (rank 250–1250)	192,529	0.2186	0.4133	0	1
Unpopular Content (rank 1250–6250)	192,529	0.7118	0.4529	0	1
Price (US dollars)	192,529	6.4795	1.0869	0.09	13.22
File Size (Mbytes)	192,529	1.4798	0.9426	0	36.95
Discount Rate	192,529	0.5985	0.0709	0.07	1.00
User-level data					
Age	238	43.5966	8.2111	30	73
Gender (1: male, 0: female)	238	0.4316	0.4963	0	1
Days Since Registered (1st device)	238	76.4443	56.5266	0	300

Notes: The unit of observation for the top two-thirds of the table is the user–content–month.

Dependent Variable

Our collected data allow consumer-level analysis to determine whether a specific individual customer has purchased a specific ebook before or on a certain date. The primary dependent variable in this paper, $PurchaseYN_{ijt}$, is a binary variable that is equal to one if a user i has bought an ebook j in month t, and zero otherwise.

Many previous studies use rank data rather than quantity or individual-level customer data due to limited opportunities to collect product sales data. Numerous studies examine Amazon.com data, which only provides relative sales information—that is, product rank data—rather than absolute sales, which is a firm's internal data, rarely shared with outside institutions. Thus these works with rank data show how product popularity and certain characteristics of testable variables affect the relative sales of products. On the other hand, our study employs individual-level customer data containing the history of each and every user's purchased ebook list with a time stamp. In other words, our analysis is specifically designed to understand content consumption behavior from the customer's perspective. Moreover, since our data explicitly describe information regarding ebooks, we can specify the characteristics of the digital product as sales quantity and price. Therefore we construct our hypotheses as testable propositions of how the sales of each product vary depending on the user profile, the number of devices owned, and the variety of device types.

Hypotheses on the likelihood of the utility of consuming digital content increasing due to an increased number and variety of devices in the user profile are consequently translated into testable propositions of the likelihood of a particular product's increased sales offering better user experience. More specifically, our testable propositions arise from the fact that users with a greater variety of screen size devices are less sensitive to the negative factors of product sales (popularity and price) or more likely to buy quality content and to demonstrate unique purchase behavior reflecting personal preferences, that is, spending their efforts buying unpopular (niche) content.

Product Characteristics

Our data provide detailed product information on each book listed in the database, including content price, file size, monthly sales, and content profile information such as publisher, author(s), length of description, and publication date. First, to measure different content consumption behaviors in a multi-screen environment, we construct the variable *Price* to identify whether content price matters (Hypothesis 2). The variable *Price* is the actual content price the consumer pays. Since our data are from a Korean ebook provider, the prices of ebooks are listed in Korean won; thus *Price* is converted to current US dollars (US$1 = 1,150 Korean won as of January 2012). Our data indicate that the prices of ebooks are up to 60% cheaper than for the hard copy versions at a bookstore; the most expensive ebook is $38 but the average non-free ebook price is $3.6.

Second, absolute sales can create huge gaps between popular ebooks: For instance, the top-selling ebook and the 20th best-selling ebook are offered to users at equal search cost, close to zero, but have over 1,000 sales gaps, altering the significance of popularity effects. Therefore we examine the popularity of ebooks by converting monthly sales amounts to sales ranks (the firm that provided our research data uses the same ranking method to display bestsellers to its customers). We create a series of dummy variables that represent specific sales rank ranges in a given month: top 50, 51–250, 251–1,250, and greater than 1,251 (1,251–6,250). We define very popular content as that which an ebook provider normally recommends or has on a list of bestsellers, that is, in the top 50, with popular content falling in the 51–250 range. We classify the lower ranges of sales rank as less popular content (251–1,250) and unpopular content (1,251–6,250). Our results regarding product selection (Hypothesis 1) are robust to a log-linear specification rank classification and demonstrate different levels of significance in content sales between popular and less popular content.

Device Classification Data

Our main analysis examines how device screen size diversity influences consumer content choice in a multi-screen environment. Adding new devices in a user profile increases the user's average usability and utility of consuming digital content. We examine two types of new device entry, small and large screen devices, with the user owning a small screen device (smartphone) in the beginning. For each individual customer in our data, the variable *NewDeviceReg* is equal to one for every month after a new device is added to the user profile (i.e., the user owns more than one device), regardless of screen size, and zero otherwise; when *NewDeviceReg* equals one, our variable *WiderDeviceEntry* is equal to one for every month after a user has registered one or more large screen devices among newly added devices, and zero otherwise.

To distinguish between small and large screens, we use the smart device classifications defined by manufacturers and previous HCI studies. Apple defines small screen devices (iPhone, iPod, and iTouch) as devices equipped with a 3- to 4-inch screen and large screen devices (iPad) as equipped with a 5- to 9-inch screen. Android OS smart devices follow similar screen sizes to differentiate between small (Android phone) and large screen devices (Android Tab or tablet PC). Buchanan et al. (2001) give an interesting analogy to distinguish between small and large information displays (screen sizes): A 2- to 4-inch display is very small for an information display suitable for very specific and concise content. Post-it Notes are a good example of a small information display in paper form. A 5- to 9-inch display, however, offers a usable interface properly balanced between the qualities of actual paper (as in hardcopy books) and a device screen suitable for displaying long or complex information. The screen size classification results from previous studies and manufacturers are robust and show strong significance regarding this paper's two major research questions.

Econometric Model

Previous research on traditional multichannel markets examines the tradeoff between the inefficiency of buying products offline and online disutility costs. Many survey-based studies utilize cross-sectional analysis to discover the tradeoffs between channels. Cross-sectional analysis is best used with data collected from numerous subjects, such as individuals or firms, at the same point in time (Brady et al. 2008). Forman et al. (2009), however, claims that identifying channel differences is challenging and it is difficult to identify separate factors with time series user behavior data via a simple cross-sectional analysis. In addition, it is difficult for a simple cross-sectional analysis to separate the effects of channel difference factors from unintended outer effects such as demand variation. For instance, a user continuously adding small screen devices may also demonstrate a purchase behavior difference by adapting user experience to a small screen display format over time. Our paper aims to analyze the purchase behavior difference in a multi-screen environment as the user adds new smart devices over 12 months and to isolate unintended effects. Thus an alternative technique is necessary to identify the factors determining purchase behavior differences derived from digital content properties (e.g., popularity and price).

Traditional multichannel market researchers suggest using a difference-in-differences approach as a perfect alternative to detect causal inference. The principle of the difference-in-differences technique (Bertrand et al. 2004) is to examine a set of units before and after treatment (in this case, adding new smart devices) within the collected time frame. Most importantly, this technique allows a control group (users with no large devices until the end of the time frame) to be set up to control for factors likely to change with time and to isolate the effect of the treatment. In addition, Forman et al. (2009) use a regression approach to the difference-in-differences method for regression controls. The basic framework starts by indexing units with *j* and time with *t*:

$$Outcome_{it} = \alpha_o + \alpha_1 Treatment_i + \alpha_2 AfterTreatment_{it} + \alpha_3 Treatment_i \times AfterTreatment_{it} + \gamma\ ControlVariables_{it} + \varepsilon_{it} \qquad (1)$$

By setting up each binary variable as zeros and ones in Equation (1), α_3 is the before–after treatment of the difference across groups. A positive α_3 indicates that the treatment has a positive effect on the outcome. With this alternative method, we can discover how different behaviors in the treatment group change as stimuli are applied. The variable $Outcome_{it}$ in our experiment determines whether an ebook is purchased and treatments determine whether new devices are added to a customer profile and whether they have a large screen. The variable $Treatment_i$ is the set of users who experience additional devices while owning a smartphone with a small screen at the beginning of the sample period. Here $AfterTreatment_{it}$ measures whether devices are added by time *t* and whether the new devices have a large screen. This method allows us to determine how much adding a new large screen device or a multi-screen environment affects the sale of pricey content to consumers compared to a single-screen environment with small screen devices only. This gives us our estimating equation:

$$\begin{aligned} PurchaseYN_{ijt} = {} & \alpha_o + \alpha_1 NewDeviceReg_{it} + \alpha_2 WiderDeviceYN_{it} \\ & + \beta_o BookRank_{jt} + \beta_1 BookRank_{jt} \times NewDeviceReg_{it} + \beta_2 BookRank_{jt} \times WiderDeviceYN_{it} \\ & + \gamma_o Price_{jt} + \gamma_1 Price_{jt} \times NewDeviceReg_{it} + \gamma_3 Price_{jt} \times WiderDeviceYN_{it} \\ & + \varphi U_{it} + \omega X_{jt} + \mu_t + \varepsilon_{ijt} \end{aligned} \qquad (2)$$

where output ($PurchaseYN_{ijt}$) is a dummy variable determining whether user *i* purchased book *j* at time *t*; $NewDeviceReg_{it}$ indicates whether user *i* added a new device in month *t* or earlier; $WiderDeviceYN_{it}$ indicates whether a new device has a large screen; $BookRank_{jt}$ is a vector of dummy variables for the sales rank of ebook *j* in month *t*, similar to how Forman et al. (2009) measure a book's popularity in a traditional multichannel market; $Price_{jt}$ is the sales price of ebook *j* at time *t*; U_{it} denotes user characteristics such as age, gender, and the number of days from the subscription date; X_{jt} is the content profile information of ebook *j,* including file size, discount rate, and the number of days since the release date; μ_t is a time fixed effect; and ε_{ijt} is a user–ebook–time idiosyncratic error term. Specifically, the control effects are designed to control possible differences between adding a new large screen device as a treatment device and adding a new small screen device as a control device, but our estimation model may still be susceptible to unmeasured factors. In this case users who add a new device may also experience a change in personal content preference and the treatment group may change differently over time than the control group (Forman et al. 2009). Difference-in-differences identification alleviates the effects of such unintended or unidentified factors by assuming that these factors affect the treatment and control groups equally (Brady et al. 2008).

Since the combinations of coefficients change as user status—that is, the number of devices (variety of screen sizes)—changes, we are interested in the interaction terms of coefficients. Forman et al. (2009) note that the coefficient of the interaction term may have a sign opposite that of the cross-partial, which makes nonlinear models such as the probit model hard to interpret. Forman et al. (2009) also note that a linear model often reduces efficiency. However, our estimation model is designed to examine data with a large number of observations and these drawbacks are therefore less likely to influence our results.

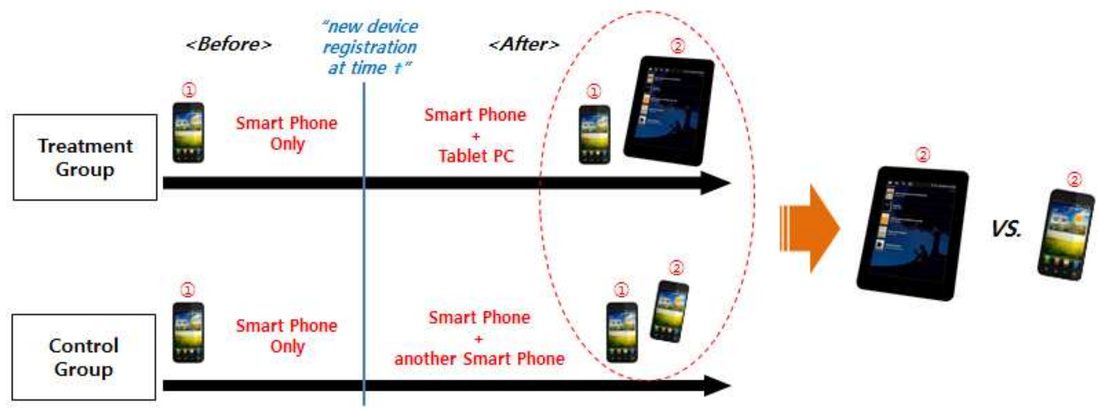

Figure 1. Natural Experiment Settings

Figure 1 illustrates the natural experiment settings of our econometric model. Our econometric model adopts a difference-in-differences method measuring the impact of multi-screen devices on user content consumption through screen size effects. Our method controls for differences in paid content purchase behavior as the number and variety of smart device users own change. Both the control and treatment groups register a single 3- to 4-inch smartphone (small screen device) in the beginning. The control group then increases the number of smart devices, with no change in screen size, representing Hypotheses 1A and 2A (*NewDeviceReg*), whereas the treatment group registers (relatively) large screen devices such as the iPad or the Android Tab, to own smart devices with a variety of screen sizes at time *t*, representing Hypotheses 1B and 2B (*WiderDeviceYN*).

Hypothesis 1A (product selection) proposes that increasing the number of devices leads users to spend more time on their smart devices and eventually increases the sales of both popular and unpopular paid content in a multi-screen environment. Since the number of smart devices does not fundamentally decrease search costs, the positive impact of increases in the sales of popular content should be greater than that of increases in the sales of unpopular content. Despite the relatively smaller impact on sales of popular content, unpopular content sales should increase as the number of smart devices registered increases. A greater number of smart devices implies a higher propensity for content usage and greater tolerance of search costs; users can afford to expend greater effort on search niche content as the number of smart devices they register increases.

Hypothesis 1B suggests that adding new devices lowers search costs and eventually increases content sales for both popular and unpopular ones. For popular content likely to be recommended or when users can access product information with close to zero search cost with any device, adding a large screen device has a weaker effect on sales than for unpopular content. Unpopular content, on the other hand, requires substantial search costs to find and access product information prior to purchase; consumer utility thus plays a big role. In fact, Hypothesis 1B states that adding a large screen device has a greater effect on content sales than adding small devices and the significance of impact on increased sales varies with product popularity due to different degrees of usability and high utility for users. We expect that adding a large screen device has a greater impact on unpopular content than on popular content, compared to adding a small device. Therefore the coefficients of the interactions of *WiderDeviceYN* and dummies for digital content *BookRank* in the unpopular category are hypothesized to be more positive than for popular digital content, compared to the coefficients of the interactions of *NewDeviceReg*—which simply represents the addition of either a small or large screen device—and *BookRank*.

Hypothesis 2A (price) tests the impact of the number of devices on niche content sales. A larger number of devices indicates greater investment in both devices and future content usage. Such a high investment in content usage directly increases content purchase performance and, consequently, tolerance of content price. In addition, tolerance of search costs increases with the number of devices and users have a higher chance of discovering high-quality information regarding paid content and no longer weight content price as the most important measure of purchase; however, content description and quality of content then become significant purchase indicators and price sensitivity decreases as the number of devices increases.

Hypothesis 2B suggests that adding a large screen device mitigates the impact on price sensitivity more than adding a small screen device because user expectations of quality content increase with higher utility of user experience since high-quality content normally comes with a higher price tag. We expect that the interactions of *NewDeviceReg* or *WiderDeviceYN* and *Price* will be positive but the impact of *WiderDeviceYN* is significantly larger than that of *NewDeviceReg*.

Results

This section shows that changes in the screen size diversity of smart devices have a substantial effect on paid content sales and the types of content sold to users. Table 2 summarizes our main results, with three hypotheses and relevant coefficients. Table 3 shows the detailed results of our difference-in-differences method on changes in user device screen size diversity and robustness to an alternative measure of smart device diversity

Table 2. Main Hypothesis and Summary of Results

Hypothesis		Relevant Coefficients	Result Summary	Supported?
Product Selection	H1A	1. Very popular x *NewDeviceReg*	Positive: 0.0648 (**)	Yes
		2. Popular x *NewDeviceReg*	Positive: 0.0462 (**)	
		3. Less popular x *NewDeviceReg*	Positive: 0.0057 (**)	
Product Selection	H1B	4. Very popular x *WiderDeviceYN*	Positive: 0.0377 (**)	Yes
		5. Popular x *WiderDeviceYN*	Positive: 0.0068 (+)	
		6. Less popular x *WiderDeviceYN*	Positive: 0.0156 (**)	
Price	H2A	7. Price x *NewDeviceReg*	Positive: 0.0069 (**)	Yes
Price	H2B	8. Price x *WiderDeviceYN*	Positive: 0.0106 (**)	Yes

*Note: The base is unpopular products. The superscripts +, *, and ** indicate significance at the 10%, 5%, and 1% levels, respectively.*

First, Hypothesis 1A implies that the number of smart devices has a positive influence on ebook sales, especially on the sales performance of less popular content. The first, second, and third interaction term coefficients in Table 2 indicate the impact of registering additional smart devices on digital content sales performance with a variety of product selections. The third interaction term coefficient, in particular, represents Hypothesis 1A. Although very popular content has the biggest influence, with 0.0648, a relevant result that supports previous research, our experiment statistically supports Hypothesis 1A, with a value of 0.0057.

The fourth, fifth, and sixth term coefficients are determined to measure the impact of device screen sizes, showing a more sophisticated impact on sales performance with content popularity, which is often a challenging problem that content providers face in increasing the sales of niche category content. Specifically, Hypothesis 1B concentrates on measuring the effect of adding a larger screen device on the sales performance of less popular content, represented by the sixth interaction term coefficient. Hypothesis 1B is statistically valid and supported. Positive influence from *NewDeviceReg* on less popular content sales is 0.0057, where *WiderDeviceReg* is 0.156, which is relatively huge. In other words, adding bigger screen devices is more helpful in boosting content sales in niche categories since an increase in screen size (term 6 in Table 2, with *WiderDeviceYN*) appears to have a more positively significant impact on the purchase performance of less popular content than the impact of increasing the number of devices (term 3 in Table 2, with *NewDeviceReg*).

Our test of the product selection effect relies on an examination of the difference between adding similar (3- to 4-inch) screen size devices and adding larger (5- to 9-inch) screen devices. Selection implies that the screen size diversity interaction coefficients for paid content ranked lower than 250 (less popular and unpopular) should be more positive for adding only wider devices (*WiderDeviceYN*) than for adding either small or large screen devices (*NewDeviceReg*), because larger screen devices are more likely to reduce product search costs and increase user utility for consuming quality information (content) than small screen devices.

Comparatively, the first and forth interaction term coefficients indicates that the sales performance of very popular content also has a positive and significantly large impact on ebook sales. Users who registered an additional smart device spend greater amounts of time with their smart devices consuming digital content; hence purchase performance on not only less popular content but also very popular content simultaneously greatly improved. Despite the increase in overall purchase performance, the increase in popular content sales is not as dramatic as the increase in less popular content sales due to *WiderDeviceYN*, especially the fifth interaction term coefficient indicates *that WiderDeviceYN* has a positive influence on popular content at the 10% significance level only because lowering the search cost for larger screen devices does not necessarily help users find more popular content. As a matter of fact, the search cost of popular content on both small and large screen devices is close to zero. The search environment for larger screen devices dramatically lowers barriers to finding unpopular content, which is favorable to less popular content consumption and leads to greater improvements in unpopular content sales. Thus, the positive magnitude of the interaction term coefficients of *NewDeviceReg* (0.0648) appears to be greater than that for *WiderDeviceYN* (0.0377), which are the opposite results for interaction term coefficients with less popular content. This statistical result is interpreted to mean the sales of very popular content does not benefit from lowering the search cost on large screen devices but mobility is a crucial factor in improving sales performance. Users can spend more time with devices that offer better mobility since high mobility reduces temporal and location constraints on the consumption of digital content. Indeed, adding a small screen smart device is more advantageous to mobility than larger screen devices such as a smart pad or PC. The interaction term coefficient of *NewDeviceReg* and very popular content should be greater than for *WiderDeviceYN*.

We provide strong evidence consistent with the product selection hypothesis. The most relevant coefficients of product selection are positive at the 1% significance level and support our first hypothesis: Increasing the number of smart devices has a positive influence on both less popular content (sales rank 250–1250) and unpopular content (sales rank over 1250). In particular, increasing smart device screen size diversity by adding wider screen devices has a stronger positive influence on the sales performance of paid content ranked 250–1250 or labeled less popular. The fourth to sixth and seventh to ninth rows of Table 3 show this most strongly: Registering an additional smartphone or large smart device increases the likelihood of purchasing relatively less popular content, as well as best-selling content, which naturally receives more user attention. As a matter of fact, the likelihood of purchasing niche content is much greater than that of purchasing popular content when a wider device is added to a user profile. These results are significant at the 1% level and support both Hypotheses 1A and 1B, respectively.

Table 3. Main Effect

Linear Regression: Independent Variables	(A) Main		(B) New device		(C) Wider device		(D) No interaction	
	Coefficient (std. error)	p	Coefficient (std. error)	p	Coefficient (std. error)	p	Coefficient (std. error)	p
Very Popular Content	0.1031** (0.00151)	0.000	0.1031** (0.00152)	0.000	0.1140** (0.00138)	0.000	0.1227** (0.00132)	0.000
Very Popular Content x NewDeviceReg	0.0648** (0.00362)	0.000	0.0802** (0.00303)	0.000				
Very Popular Content x WiderDeviceYN	0.0377** (0.00547)	0.000			0.0921** (0.00460)	0.000		
Popular Content	0.0252** (0.00087)	0.000	0.0252** (0.00087)	0.000	0.0313** (0.00081)	0.000	0.0344** (0.00078)	0.000
Popular Content x NewDeviceReg	0.0462** (0.00234)	0.000	0.0489** (0.00198)	0.000				
Popular Content x WiderDeviceYN	0.0068+ (0.00378)	0.0741			0.0472** (0.00320)	0.000		
Less Popular Content	0.0062** (0.00045)	0.000	0.0062** (0.00045)	0.000	0.0068** (0.00042)	0.000	0.0081** (0.00041)	0.000
Less Popular Content x NewDeviceReg	0.0057** (0.00128)	0.000	0.0113** (0.00108)	0.000				
Less Popular Content x WiderDeviceYN	0.0156** (0.00206)	0.000			0.0208** (0.00173)	0.000		
Price	-0.2137** (0.00038)	0.000	-0.2134** (0.00038)	0.000	-0.2124** (0.00034)	0.000	-0.2102** (0.00033)	0.000
Price x NewDeviceReg	0.0069** (0.00062)	0.000	0.0115 (0.00056)	0.000				
Price x WiderDeviceYN	0.0106** (0.00088)	0.000			0.0158** (0.00080)	0.000		
Observations	192,529		192,529		192,529		192,529	
R-Squared	0.8542**		0.8537**		0.8535**		0.8525**	

*Notes: The base is unpopular ebooks ranked 1,250 and up. The superscripts +, *, and ** indicate significance at the 10%, 5%, and 1% levels, respectively.*

This result suggests that smart device screen size diversity substantially reduces search costs and that changes in both screen size diversity and the number of devices shape consumer content choices. In other words, content providers can determine whether a group of users has an increased demand for niche content; niche content should be recommended to users who own a number of smart devices with a variety of screen sizes. This implication is economically important since content providers sell proportionately more paid niche content than top sellers and a largely concentrated content sales distribution effectively stimulates sales profits (Brynjolfsson et al. 2011).

Second, we examine how screen size variety influences the price sensitivity of paid content. Hypothesis 2 (content price) conjectures that greater quality content needs decrease the price sensitivity of paid content purchases as the number of smart devices and the diversity of screen sizes increases. Content price sensitivity implies that the screen size diversity interaction coefficients for paid content prices should be more positive when adding a wider device (*WiderDeviceReg*) than when adding either a small or large screen device (*NewDeviceYN*) due to greater expectations of better user experience in a comfortable environment. The seventh interaction coefficient term in Table 2 dictates Hypothesis 2A and the eighth term dictates Hypothesis 2B regarding content price. These two interaction coefficients strongly support the content price hypothesis. All relevant coefficients of content price are positive at the 1% significance level. Moreover, increases in the number of smart devices from the addition of wider screen devices appear to have a relatively stronger influence on the sales performance of expensive paid content than simply the addition of new devices. This observation can be interpreted to mean that registering an extra, wider device leads to an increased number of devices and screen sizes, both impacting paid content purchase behavior, thus effectively lowering price sensitivity. The 10th to 12th rows of Table 3 show that the likelihood of purchasing paid content increases by 0.0069 as the number of registered devices increases by one and increases by 0.0106 if a newly registered device is a wider device. These results support both Hypotheses 2A and 2B at the 1% significance level, respectively.

Our results suggest that lower search costs and a higher chance of consuming quality information are associated with decreased sensitivity to paid content price. This means that content providers can build business strategies to sell paid content by segmenting user groups based on the number of devices and variety of screen sizes registered in users' profiles. Since reproducing digital content costs next to nothing, selling pricey content is largely profitable for content providers. In addition, content providers can design marketing promotions for users to become multi-screen device owners with a variety of screen sizes and stimulate the need for better usability and expectations of quality content. Consequently, content providers should secure greater numbers of users who have a greater probability of consuming paid content with less price sensitivity because acquiring a substantial group of loyal customers guarantees success in their business.

Lastly, columns (B) to (D) in Table 3 show evidence that reflects what firm managers would conclude from the baseline situation with no interaction (column (D)) to the independent effect of registering new devices only (column (B)) and registering wider devices only (column (C)). In short, each independent effect demonstrates results with similar significance levels and signs as for the main effect, in column (A). Therefore these results are robust to various specifications. User characteristics, content profile information, and time fixed effects are all controlled for when testing each effect.

Conclusion

Our results provide empirical support to identify factors affecting digital content purchase decision making. We find that users owning smart devices more suitable for convenient content usage have a positive impact on content purchase decisions. Our empirical results also identify a set of potentially useful implications for content providers: A multi-screen environment, that is, user ownership of a number of smart devices, has a positive magnitude of content purchase performance from experiments and a variety of screen size devices (wider devices), in particular, has a greater impact on content sales.

From our understanding, our study is the first to attempt to empirically analyze the effects of owning multiple smart devices with respect to the number of devices and a variety of device screen sizes in a multi-screen environment. Since numerous new smart devices are continually being introduced in the digital market to support digital content consumption, more users, especially ebook consumers, own multiple devices with a variety of screen sizes rather than a single smart device. Consequently, users owning multiple smart devices spend more time consuming digital content; promoting effective content sales for such customers is therefore critical to the success of content providers.

The results can be described from two perspectives: (i) the effect of increasing the number of devices and (ii) the effect of increasing the screen size or variety of smart devices. The first effect (i) implies that the consumption of paid content increases as the number of registered smart devices increases. As a user registers new devices and owns multiple devices, the user spends significantly more time reading ebooks. Spending more time with smart devices implies an increased need to purchase ebook content accordingly and a decrease in price sensitivity when purchasing paid content. Therefore a multi-screen environment creates greater economic value in the digital content market. The second effect (ii) implies increased usability and utility for users consuming digital content. A large screen device evidently provides a better user environment for reading ebooks and an improved content search interface where users can find ebooks they want to purchase with relatively less effort and time than with a smaller screen device. This eventually lowers search costs and increases the likelihood of purchasing both relatively pricey content and less popular content, or niche category ebooks. Hence encouraging users to add larger screen devices to become multiple device owners creates remarkable value in the digital content market.

Our paper contributes to three areas of research. First and most importantly, we provide empirical support for existing HCI theories of user behavior and purchase behavior depending on user screen sizes (Basil 1994; Detenber et al. 1996; Lang 1980; Lombard 1995; Lombard et al. 1995; Reeves et al. 1999). By providing evidence of the importance of registered device variety in considering user profiles and the relative magnitudes of mobile content properties such as price, we provide further insights from a business perspective into the results that often depend on these parameters. Second, our paper contributes to the empirical literature on online consumer behavior and provides managerial implications for mobile content providers, aggregators, and generators offering mobile products in a multi-device environment. Most prior works focus on user response from psychological and media perspectives in a fixed environment with a personal digital assistant or either a small or large screen providing a service or content design implication (Acton et al. 2004; Albers et al. 2002; Arning and Ziefle. 2006; Bridgeman et al. 2001; Buchanan et al. 2001; Chen et al. 2005; Maniar et al. 2008; Lombard et al. 1997; Sweeney and Crestani 2006; Stafford 2009; Stahl and Maass 2006). Our study explores how a variety of screen sizes affects mobile content purchase performance from a business intelligence viewpoint.

In traditional studies about the digital economy, content price is known as a negative factor affecting online customer purchase decisions; however, we find that (i) user experience with high utility and usability in a multi-screen environment through owning various screen size devices decreases the price sensitivity of purchasing digital content. Furthermore, (ii) wider screen device owners in a multi-screen content market are more likely to purchase niche products and show a more widely concentrated sales distribution from a product selection perspective. Such purchase behavior is economically interpreted to mean that owning a large screen device among a variety of smart devices not only improves convenience in content usage, but also reduces the search costs to acquire desired content with quality information on a timely basis. Therefore users with a variety of screen size devices have a higher utility for content purchases reflecting personal preferences and a higher probability of buying unpopular content than with a small screen device such as a smartphone. From a managerial perspective, content providers can thus identify users who cover content sales in the long-tail categories (Brynjolfsson et al. 2011) from the number of smart devices registered in their profile status and effectively recommend niche content.

According to the Koekkok's DISTIMO report (2011), the digital content market is a billion dollar market in the US alone. We believe our findings provide important implications for managers who wish to build a dedicated business strategy for paid content sales. First, encouraging new and existing online users to register more screen size varieties of smart devices is crucial to the success of content providers at the beginning stage of the content market. Although a marketing campaign to add more devices to a user profile entails financial costs, the expected volume of content purchase will increase as the variety of registered smart devices improves users' multi-screen infrastructure. In other words, turning existing users into loyal customers will bring higher profits for content providers in the long run. Second, the number of registered devices and the variety of screen size devices and multi-screen capabilities are important factors in the target customer group selection for a high-quality, high-price content marketing strategy. Thus a content provider can predict the response and purchase success rates of paid content recommendation campaigns from the level of multi-screen capabilities in a user profile. Third, from a digital economy perspective, an aggressive long-tail content marketing strategy can be deployed, depending on the level of multi-screen capabilities. Large screen device owners take advantage of a better searchable interface for niche (less popular) content, which encourages customers to be purpose oriented with definite content preferences and needs and have higher expectations of better user experience from quality content, which often reduces price sensitivity. Therefore recommending content in long-tail categories to users with high levels of multi-screen capabilities is highly desirable.

Our study targets ebook sales data to perform an empirical analysis. As with any empirical work, the depth of our analysis has considerable limitations. To preferentially determine detailed multi-screen effects, the data should capture vivid device registration behavior from the history of user profiles, but users who register more than three smart devices are rare in our observed dataset. Therefore our analysis concentrates on the purchase behavior of users who originally registered one smart device in the beginning and added another one within a year. Our study aims to evaluate the influence on perceptions of content price and purchase behavior differently, depending on content popularity as the number of smart devices or the variety of device screen sizes increases. Accordingly, future studies should collect more data at the individual level, describing more diverse content purchase performance in a multi-screen environment, to produce more reliable empirical results. Although our results are likely to be informative about digital content in general, a similar experimental setting should be applied to other types of digital content that may have different characteristics, such as music and video, to confirm the role of multi-screen capabilities.

Lastly, several extensions of further research are possible. One is to compare the content consumption behavior of multi-device and single device owners . Understanding the behavior of single device owners is advantageous for the following reason: Examining screen effects among single device customers can increase the generalizability of our results. We can determine the difference in purchase behaviors between single device (either small or large screen) owners and multi-device owners (two small or large devices versus small to large versus large to small screen devices). Such analysis allows us to understand possible migration effects to small or large devices among multi-screen users if they behave similarly to single device owners; otherwise, an in-depth, detailed analysis of our results is possible and single and multi-device owners should be treated differently. Another possible extension is to incorporate market competition into the control variables. A choice model as a competition model gathering competitors' sales data—such as the total number of ebook sellers, the average price of a particular digital item, and the relative advertising spending of different sellers—allows one to understand whether user decisions are based on optimizing over given available options. Understanding how consumers purchase certain paid content in various market situations from user-level data analysis with the user choice model would significantly contribute to digital content sales research and strengthen our empirical analysis.

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