DOES THE MOBILE CHANNEL CANNIBALIZE THE ONLINE CHANNEL? AN EMPIRICAL INVESTIGATION

Completed Research Paper

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Abstract

Despite the growing importance of the mobile channel, driven by the widespread use of the mobile Internet and smartphones, we have a limited understanding about the performance impact of introducing the mobile channel. We use a unique panel dataset from a large e-marketplace to investigate the impact of a mobile channel introduction on the existing online channel and overall firm revenue. Based on a multivariate baseline analysis with vector auto-regression, we find that overall, the mobile channel enhances the online channel and generates new demand, thereby increasing firm revenue; additionally, we find that this impact is present only in the consumers who adopted the mobile channel. More importantly, our results suggest that the impact of the mobile channel depends on two product characteristics – time-criticality and information intensity –, which are directly related to the unique capabilities of the mobile channel. We find that for products with high time-criticality and low information-intensity, the mobile channel cannibalizes the online channel, although the net impact of the mobile channel on the total revenue is positive because of its large demand generation effects. On the other hand, for products with low time-criticality, we find a complementary impact of the mobile channel on the online channel. We also find that this impact is greater in products with high information-intensity.

Keywords: Mobile channel, mobile commerce, multi-channel strategy, cannibalization, vector auto-regression with exogenous variables, multivariate baseline analysis

Introduction

The explosive penetration of mobile devices, together with the growth of mobile networks is one of the most prominent trends in IT. More than half of Facebook's users access this social network through a mobile device (Garver, 2012). According to a recent study by Cisco (2012), globally, the mobile network speed grew 66 percent in 2011, and the mobile data traffic in 2011 was eight times the size of the entire global Internet in 2000. The study estimates that the number of mobile devices will exceed the world's population in 2012, and that the mobile data traffic will increase 18-fold between 2011 and 2016.

With the prevalence of mobile devices and networks, mobile channels are rapidly emerging as a new commerce venue. Global mobile transaction values are expected to reach $617 billion, with 448 million users by 2016, up from $105.9 billion, with 160.5 million users in 2011 (Gartner, 2012). Forrester Research (2011) projects that mobile commerce (m-commerce) sales in the US are expected to hit $31 billion by 2016, with 40 percent growth each year from 2011, accounting for 7 percent of e-commerce in 2016 (Mulpuru, 2011). eBay estimates that its 2012 global mobile gross merchandise volume (GMV) will surpass $8 billion, up from $5 billion in 2011 (Brewer-Hay, 2012).

While e-commerce firms are increasingly introducing mobile channels following their competitors,[1] adding mobile channels to traditional e-commerce channels (hereafter, online channels) based on the stationary Internet is a crucial decision for firms. Without systematic multi-channel strategies, the implementation of m-commerce channels might result in merely another competitive necessity, in which costly IT investment generates no gains in competitive advantage or performance as a consequence of the competitive pursuit of IT (Lucas, 1999), for instance, as in the case of the bank automatic teller machine (ATM) (Clemons, 1990). Further, the introduction of mobile channels may transform the users' information search and transaction behaviors (Ghose et al., 2012) and may cause interactions with existing channels, possibly leading to the cannibalization of online channels.

Nevertheless, we are lacking in rigorous empirical studies on this emerging critical issue, mainly due to the paucity of necessary data. The objective of this study is to investigate the performance impact of a mobile channel introduction for e-commerce firms, based on a unique and novel panel dataset from a large e-marketplace, which initially operated an online channel only and introduced a mobile channel in June 2010.[2] The dataset includes all transactions through both the online and mobile channels by a sample of customers between March 2009 and May 2011. Using a multivariate baseline analysis based on vector auto-regression with exogenous variables (VARX), we compare various performance measures, including the number of unique customers, the number and size of orders, cancellations, and returns before and after the mobile channel introduction. Moreover, we examine whether the two product characteristics, time-criticality and information-intensity influence the performance impacts of the mobile channel by examining various product categories.

To the best of our knowledge, this is the first study to measure the effects of a mobile channel introduction on e-commerce firm performance and to investigate the performance implications of the channel introduction for different types of products. From a methodological viewpoint, we introduce and apply a multivariate baseline analysis with VARX, which has recently been used in marketing literature (e.g., Pauwels and Neslin, 2011). The analytical approach in this study could provide the IS society with a novel, promising method to quantify the impact of an IT intervention such as an IS implementation on multiple performance variables.

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[1] According to a survey by Shop.org/Forrester Research (2011), 91 percent of online retailers in the US have a mobile strategy in place or in development. Forty-eight percent of retailers surveyed report having a mobile website; 35 percent have deployed an iPhone app; and 15 percent offer an Android app.

[2] An e-marketplace is an Internet site where many sellers and buyers get together to conduct transactions (e.g., eBay).

Theoretical Background

Performance Impacts of Channel Introduction

Although developing and implementing a multichannel strategy is a critical issue for firms, there have been only a few previous empirical studies on the performance impacts of introducing a new channel. Based on a sample of 85 newspapers that added Internet channels, Deleersnyder et al. (2002) find that no significant cannibalization occurs in offline channel revenues. Biyalogorsky and Naik (2003) analyze data from a music retailer, Tower Records, which opened a sales-oriented website in addition to its offline store operation, and find that the introduction of a selling site does not harm the firm's offline retail sales. Danaher et al. (2010) examine whether digital distribution of media contents cannibalizes the online sales of physical DVD box sets of the contents. From an analysis of the Amazon.com sales rank of NBC television season box sets before and after NBC's removal of its contents from iTunes in December 2007, they find no significant change in the sales rank, concluding that the digital distribution channel (iTunes) does not substitute for the physical product channel sales. Pauwels and Neslin (2011) assess the revenue impact of adding offline stores to the existing catalog and Internet channels of a firm. By applying a multivariate baseline method, they find that offline stores cannibalize catalog sales, but have no impact on Internet sales. Similarly, Avery et al. (2012) examine the impact of adding offline stores to the direct channels of a firm. They analyze data from a multichannel retailer of high-end apparel, accessories, and furnishing, which opened new retail stores in addition to existing catalog and Internet channels. Using matching methods, the authors find that the presence of a retail store decreases sales in the catalog, but not the Internet channel in the short run, but increases sales in both channels over time.

These studies suggest that the performance impact of introducing a new channel in a multichannel environment differs, depending on the channel composition. Further, the order of the channel introduction may matter, even with the same channel composition (Avery et al., 2012; Pauwels and Neslin, 2011). As such, it is not clear whether the mobile channel introduction will cannibalize or enhance the performance of the online channel, and what the overall impact will be on firm performance. On one hand, the introduction of a mobile channel can provide an alternative purchase channel for consumers to buy some products that they would otherwise buy through an existing online channel, thereby leading to cannibalization of the online channel. On the other hand, the introduction of a mobile channel can enhance consumers' information search ability by allowing consumers to search for product information anywhere, anytime they want, which can in turn trigger additional purchases in the online channel. For example, a consumer may browse the mobile channel during her commute and find an attractive product. Then, she can purchase the product after more intensive search through the stationary Internet at home. The latter scenario is supported by a recent study from Google and Ipsos OTX (2011), which finds that 74 percent of smartphone users have made a purchase as a result of performing searches on smartphones, and among them, 59 percent have purchased products online using PCs and 35 percent have purchased products on smartphones.

In order to better assess whether cannibalization or enhancement effects will predominate in the case of the mobile channel, we next examine the capabilities of the mobile channel vis-à-vis the online channel.

Channel Capabilities

Channel capability is defined as "an enabling characteristic of a channel that allows consumers to accomplish their shopping goals" (Avery et al., 2012, pp. 96-97). Avery et al. (2012) suggest that each capability of a new channel can be evaluated on two dimensions: (1) whether a given capability of the new channel substitutes for or complements the capabilities of the preexisting channels, and (2) whether a given capability is quickly apparent to the consumer or must be learned through experience. The first dimension helps assess the direction of the effect in terms of whether the new channel will cannibalize demand in the preexisting channels (substitutive capabilities) or create new incremental demand for them (complementary capabilities). The second dimension is related to the timeframe when we should expect to observe the effect, that is, a short-term effect for a conspicuous capability, and a long-term effect for an experiential capability.

While the channel capability framework is conceptually simple, it is difficult to apply. This is because typically each channel has many different kinds of capabilities, and some of them may generate complementary effects, while others may involve substitutive effects. Further, each effect differs in its magnitude. For an assessment of the net effect of a new channel introduction, one needs to put together each effect related to each capability, which can be very challenging. However, in the case of interaction between a mobile channel and an online channel, the task is simpler because the number of capabilities relevant to the assessment is limited, as is described below.

Access and Search Capabilities of Mobile and Online Channels

Unlike the case of offline and online channels, mobile and online channels share most capabilities. For example, both channels offer the same product assortment, no ability to touch and feel products, and no face-to-face communication with the retailer. This is because both channels are, in essence, electronic media for product search and transactions. In addition, every product by each seller is offered at the same price in both channels, as is the case for the e-marketplace we study.

However, there are distinct capabilities between online and mobile channels that result from inherent differences between the stationary Internet and the mobile Internet. The mobile Internet can be characterized as easier to access, but harder to browse, compared with the stationary Internet. Mobile devices are, by definition, portable and not fixed to a location; and mobile devices typically have smaller screens than PCs (Ghose et al., 2011; Venkatesh et al., 2003). In particular, mobile channels are different from online channels in two capabilities: *access* and *search*.

First, consumers can access the mobile channel wherever and whenever they want. This is a critical capability in favor of the mobile channel, which we call *ubiquitous access capability* (vs. *constrained access capability* of the online channel). While e-commerce based on the stationary Internet can overcome geographic distance, enabling buyers to access remote sellers (Afuah and Tucci, 2002), buyers' locations should be fixed to places that have PCs and Internet connections. On the other hand, buyers can access the mobile channel without such a constraint, thereby supporting time-critical activities (Venkatesh et al., 2003) and facilitating immediate transactions.

Second, due to the small screens and low usability of mobile devices (Venkatesh and Ramesh, 2006), information search through mobile channels is substantially limited, compared with online channels. For example, Duchnicky and Kolers (1983) showed that people could read 25 percent faster on larger screens than on screens that were one-third the size. Jones et al. (1999) found 50 percent less effectiveness in completing tasks when users performed them on small screens compared to tasks on larger screens. Such a limitation may also hamper longer and complex uses of m-commerce (Ghose et al., 2011). This tendency is intensified by the transitive nature of mobile Internet usage. Therefore, e-commerce firms usually offer their mobile websites or apps in streamlined forms, compared to PC version sites. In summary, mobile and online channels are essentially different in their information search capabilities, which we refer to as *extensive information search capability* for the online channel and *limited information search capability* for the mobile channel.

Channel Capabilities and Interactions between Mobile and Online Channels

Although mobile channels have a limited search capability, they enable consumers to overcome the constrained access capability of the online channel, thereby facilitating ubiquitous access to the e-marketplace. Therefore, we expect the total number of orders to increase after the mobile channel introduction. The incremental orders can be generated through both mobile and online channels. In the former case, the mobile channel would work as a new revenue source. In the latter case, the mobile channel complements the online channel in such a way that its ubiquitous access capability, coupled with its limited information search capability, triggers additional searching and purchasing via the online channel.

In contrast to the increase in the number of orders, the order size (the average monetary amount of orders) is expected to decrease with the mobile channel introduction. According to the economics of information search theory, consumers continue to search for information as long as the marginal cost of the search is smaller than the marginal benefit (Stigler 1961). Thus, lower search costs due to the ubiquitous access capability of the new mobile channel would increase consumer search. In the presence of substantial price dispersion online (e.g., Brynjolfsson and Smith, 2000; Clemons et al. 2002), increased search would lead to lower- priced products (that is, a smaller order size, on average). This is particularly the case for an e-marketplace, where similar (often the same) products are offered by many sellers at different prices.[3] To sum up, we expect that the number of orders will increase, whereas the order size will decrease after the mobile channel introduction.

Product Characteristics and Channel Capabilities

In order to assess the differential impact of the mobile channel introduction across different product categories, we define two product characteristics that are closely related to the two capabilities of mobile channels: the *time-criticality of transactions* and the *intensity of product information* (see Figure 1). The time-criticality of a transaction is related to the change in the buyer's utility from a product, depending on the time of purchase. Some products are characterized by strong time constraints for purchase (and therefore consumption), while others are not. For example, the value of Christmas cards declines sharply after Christmas; everyone wants a travel package that matches her vacation schedule; and concert tickets may be useless after one's wedding anniversary. As illustrated in these examples, for some product categories, the buyer's utility decreases drastically after a point in time that may be specific to the buyer. Some people may want to buy clothes for gifts on specific days. However, many more consumers purchase clothes for their own utilitarian purposes, in which case time constraints are not critical and the change in utility is at most, incremental over time. Thus, clothes can be regarded as products with low time-criticality.

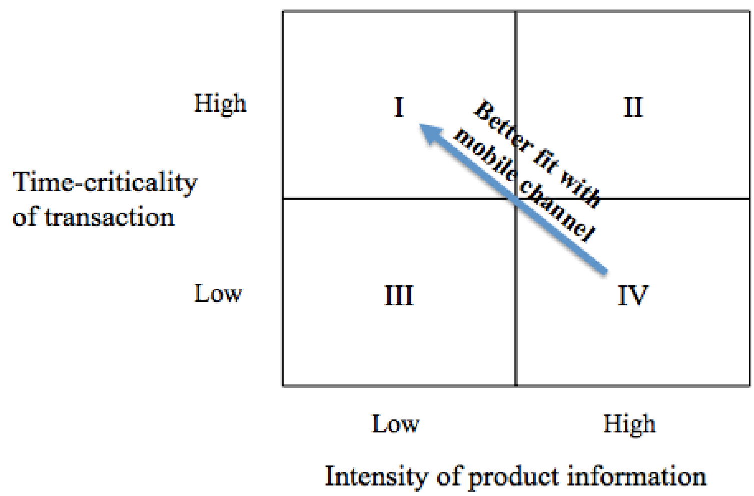

Figure 1. Product Characteristics and Fit with the Mobile Channel

Product information intensity refers to the amount of information that is required to be processed before making purchase decisions. Some product categories (e.g., home furniture and cameras) involve extensive search in terms of the number of pages viewed and the total time spent on search, whereas other categories (e.g., health/beauty products) entail much less of an extensive search (Huang et al., 2009).

Quadrant I in Figure 1 correspond to those products characterized by a high level of time-criticality and a low level of information-intensity. The mobile channel can provide an excellent access medium for such products, thanks to its ubiquitous access capability. A low level of information-intensity indicates that the limited information search capability of the mobile channel may not work as an obstacle to transactions of these products through the channel.

[3] It may be argued that increased search will reduce perceived risk by consumers for high-priced products, thereby increasing the average order size (Verhoef et al., 2007). This is likely when consumers can obtain additional valuable information from the new channel that is not available in the existing channel. However, this possibility is low in our research context because all of the information in the mobile channel is already available in the online channel.

This implies that the mobile channel fits greatly with these products, and the two capabilities of the mobile channel would substitute for their corresponding capabilities of the online channel. Therefore, we expect the mobile channel to cannibalize the online channel while generating a substantial new demand of its own.

As the opposite case, let us consider Quadrant IV, where the mobile channel capabilities may not exert any influence on the online channel capabilities. Because products in this quadrant are not time-critical, the ubiquitous access capability of the mobile channel would be less valued, compared to time-critical products. Further, a high level of information intensity indicates that information search through the mobile channel is not likely to be sufficient in making purchase decisions for products. Given that the mobile channel would show the lowest fit for these products, we expect that the demand impact of the mobile channel introduction on the online channel would be the smallest among the four product categories.

Methodology

To analyze the impact of the mobile channel introduction on the preexisting online channel and the e-marketplace, we need to compare the performance variables with and without the mobile channel introduction. Since we can observe the outcome with the mobile channel introduction, the essence of the analysis is how to assess the potential outcome without the mobile channel introduction. To assess the potential outcome, we employed a multivariate baseline analysis based on vector auto-regression with exogenous variables (VARX). A baseline analysis approach has been adopted to predict not only a single target variable (e.g., item sales in a store) (Abraham and Lodish, 1993), but also multiple target variables that influence one another over time (Pauwels and Neslin, 2011). We used the following analysis procedure described in Pauwels and Neslin (2011).

Step 1: Identify the Main and Control Variables

First, we identified the variables of interest that are relevant to the market outcome. *Number of Unique Customers*, *Number* (and *Size*) *of Orders*, *Cancellations*, *Returns* and *Exchanges* are identified as the focal variables. Then, we identified a number of control variables that either can endogenously or exogenously influence the focal variables: *Number of Unique Sellers*, *Market Size*, *Level of Market Competition*, *Market Share* (of the e-marketplace), *Number of Promotions*, and *Seasonal Dummies* (daily).

Step 2: Preliminary Tests on the Main and Control Variables

Before estimating the baseline model, we conducted preliminary tests on the variables in our model to figure out whether they are stationary or evolving by using the Augmented Dickey-Fuller test. Once the variables are identified as evolving, we then need to take the first differences before including them in the model.

Step 3: Estimation of Baseline Model

We employed a VARX model to extrapolate the endogenous variables into the post-introduction period. VARX models are well-accepted in marketing for forecasting when several endogenous and exogenous variables are involved (Dekimpe and Hanssens, 1999; Pauwels et al., 2004). We model all main variables and *Number of Unique Sellers* as endogenous. Thus, the total number of endogenous variables is 12. Then, the general form of the model we need to specify is,

$$\begin{bmatrix} NUC_t \\ NUS_t \\ NO_t \\ SO_t \\ NCB_t \\ SCB_t \\ NCA_t \\ SCA_t \\ NR_t \\ SR_t \\ NE_t \\ SE_t \end{bmatrix} = \begin{bmatrix} C_1 + \sum \chi_{1d} S_{dt} \\ C_2 + \sum \chi_{2d} S_{dt} \\ C_3 + \sum \chi_{3d} S_{dt} \\ C_4 + \sum \chi_{4d} S_{dt} \\ C_5 + \sum \chi_{5d} S_{dt} \\ C_6 + \sum \chi_{6d} S_{dt} \\ C_7 + \sum \chi_{7d} S_{dt} \\ C_8 + \sum \chi_{8d} S_{dt} \\ C_9 + \sum \chi_{9d} S_{dt} \\ C_{10} + \sum \chi_{10d} S_{dt} \\ C_{11} + \sum \chi_{11d} S_{dt} \\ C_{12} + \sum \chi_{12d} S_{dt} \end{bmatrix} + \sum_{k=1}^{K} A^k \times \begin{bmatrix} NUC_{t-k} \\ NUS_{t-k} \\ NO_{t-k} \\ SO_{t-k} \\ NCB_{t-k} \\ SCD_{t-k} \\ NCA_{t-k} \\ SCA_{t-k} \\ NR_{t-k} \\ SR_{t-k} \\ NE_{t-k} \\ SE_{t-k} \end{bmatrix} + B \times \begin{bmatrix} MSZ_t \\ LMC_t \\ MS_t \\ NP_t \end{bmatrix} + U_t$$

where NUC_t = *Number of Unique Customers* in period *t*, NUS_t = *Number of Unique Sellers* in period *t*, NO_t = *Number of Orders* in period *t*, SO_t = *Size of Orders* in period *t*, NCB_t = *Number of Cancellations Before Payments* in period *t*, SCB_t = *Size of Cancellations Before Payments* in period *t*, NCA_t = *Number of Cancellations After Payments* in period *t*, NCB_t = *Size of Cancellations After Payments* in period *t*, NR_t = *Number of Returns* in period *t*, SR_t = *Size of Returns* in period *t*, NE_t = *Number of Exchanges* in period *t*, SE_t = *Size of Exchanges* in period *t*, MSZ_t = *Market Size* in period *t*, LMC_t = *Level of Market Competition* in period *t*, MS_t = *Market Share* in period *t*, NP_t = *Number of Promotions* in period *t*, S_{dt} = 6 daily seasonal dummies, A^k = (12×12) matrix of coefficients for endogenous variables, *B* = (12×4) matrix of coefficients for exogenous variables, and U_t = (12×1) vector of error terms.

The number of lags, *k*, is determined by such criteria as the Schwarz information criterion (SC) or the Akaike information criterion (AIC) after running the model. Also, each lag should be carefully examined with the diagnostic tests on residual autocorrelation. Lastly, each endogenous variable needs to be empirically verified using Granger Causality tests.

Step 4: Project Baseline to Post-Mobile Channel Introduction Period, and Compare the Predicted Values with Actuals

The estimated VARX model extrapolates all endogenous variables into the post-introduction period. The difference between the baseline value and the actual value on each main variable is examined. Finally, the revenue without the mobile channel introduction is computed and compared with the actual revenue.

Data and Variables

We obtained two large datasets from a large e-marketplace in South Korea that had initially provided an online channel only and launched a mobile channel later on. Each of the two datasets contains users' transaction records including orders, cancellations before and after payments, exchanges, and returns. The first dataset contains a random sample of 30,000 users who did not adopt the mobile channel (the non-adopter group *hereafter*) until one-year after the introduction of the mobile channel (t_2), and their entire transaction records from March 2009 to June 2011. The second dataset contains a random sample of 30,000 users who adopted the mobile channel before t_2 (the adopter group *hereafter*), and their entire transactions records made through the online and mobile channels during the same period as the first dataset. Our datasets contain transaction records before and after the introduction of the mobile channel (t_1), which gives us an ideal opportunity to explore the impact of the mobile channel introduction on the online channel performance in a quasi-experimental setting. Figure 2 shows the composition of our datasets. Since our main interest is in examining the impact of the mobile channel introduction on the purchase behaviors of existing customers, we use the second dataset for our main analysis and we use the first dataset to check the validity of our baseline model.

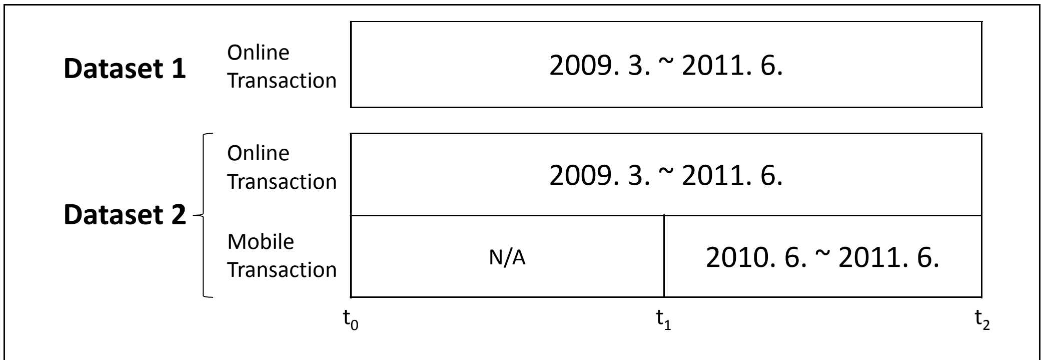

Figure 2. Composition of the Datasets

When estimating the baseline model, the addition of new customers between t_0 and t_1 may confound the effect of the mobile channel introduction on existing customers, since their joining may be associated with their intention to purchase products at the time of sign-up. We sign up at Amazon.com, for example, when we want buy a book at the site. Furthermore, newcomers' purchase patterns may be different from those of existing consumers (Avery et al., 2012). Therefore, including the customers who joined between t_0 and t_1 in the sample may contaminate the impact of the mobile channel introduction on the existing customers. Fortunately, our dataset allows us to focus on existing customers who had already joined the e-marketplace before t_0 (n=12,239). By removing the new customers added between t_0 and t_1, we can effectively tease out the effect of the mobile channel on the purchase behaviors of the existing customers.

Table 1 shows the daily average values of our main variables *before* and *after* the mobile channel introduction in the sample.

Number of Unique Customers in the online channel was 285.9 before the mobile channel introduction, and was 422.9 after the mobile channel introduction. That is, among the 12,239 existing customers, approximately 286 (423) customers made a purchase every day on average before (after) the mobile channel introduction. It looks as if there were a huge impact of the mobile channel introduction on the number of unique customers, but we cannot conclude anything, since this increase may be due to either a fast upward trend of the number of unique customers or other factors that affected the number of unique customers and changed over time. This is why we use the baseline model approach. The daily average numbers of orders, cancellations, exchanges and returns also increased substantially after the mobile channel introduction. The daily average size of orders (also, cancellations, exchanges, and returns), measured in Korean currency (KRW),[4] refers to the average basket size in terms of price. Most of the sizes decreased after the mobile channel introduction, which may indicate transaction dispersion between the two channels.

We include several control variables in the baseline model. We include the *Number of Unique Sellers*, which counts unique seller identities in the transactions, as an endogenous variable, since there is a positive feedback relationship between the number of sellers and the number customers (Grieger, 2003). We control for both the *market size* and the *market share* of the e-marketplace to account for the fast growth of the market and the e-marketplace. Failure to control for these variables would underestimate our baseline, thereby overstating the impact of the mobile channel introduction. We obtained monthly *market size* from Statistics Korea, and yearly *market share* from the Fair Trade Commission Korea. Since we need daily data for each of the two variables, we interpolated them based on the finite number of monthly and yearly points with an assumption of continuous and linear changes over time. We also control for *market competition*, given that it directly affects customer retention and purchase behaviors. To measure market competition, we calculated Herfindahl indices using the predicted market shares of four major players from the interpolation. The four major players cover over 99% of the shares of the overall market. We control for the number of promotions, as it can affect our main variables. Finally, we include 6 daily dummies in the model, since we found 7-day seasonality.

[4] 1 USD = 1,110.50 KRW at the time of 6 p.m. Oct 12, 2012.

Table 1. Daily Average Values of the Main Variables				
Time Period		Before Mobile Channel Introduction (2009/03/01~2010/05/31)	After Mobile Channel Introduction (2010/06/01~2011/05/31)	
Transaction Channel		Online	Online	Mobile
Number of Unique Customers		285.9 (91.4)	422.9 (109.2)	76.0 (62.0)
Orders	Number	581.6 (230.1)	1,024.5 (270.6)	120.4 (111.3)
	Size	34,396.8 (13,706.7)	29,899.5 (6,500.4)	26,038.4 (20,347.6)
Cancellation Before Payment	Number	39.4 (19.2)	63.1 (25.5)	10.2 (11.3)
	Size	44,187.9 (227,919.3)	40,071.5 (74,016.6)	39,411.3 (65,443.8)
Cancellation After Payment	Number	31.9 (15.1)	53.5 (17.6)	5.3 (5.5)
	Size	59,297.9 (43,606.8)	54,274.2 (25,775.0)	39,356.0 (36,660.8)
Exchange	Number	2.7 (2.1)	3.9 (2.8)	0.3 (0.8)
	Size	36,845.5 (42,752.8)	39,403.7 (47,158.7)	31,498.4 (26,464.0)
Return	Number	8.9 (6.3)	14.9 (7.3)	1.2 (1.9)
	Size	53,626.1 (108,369.2)	41,035.1 (33,878.7)	35,090.5 (41,901.5)

Results

Impacts of Mobile Channel Introduction on the M-Commerce Adopters

Estimating the VARX model

The lag order for both endogenous and exogenous variables is selected as 1 based on the SC and AIC. The unit root analysis results show that no root lies outside of the unit circle and the VARX model satisfies the stability condition, that is, all variables follow stationary processes. VAR Granger Causality tests confirm that all endogenous variables are caused by other variables.

Baseline projections vs. actual transactions

We first applied the VARX model to the non-adopter group, who joined the e-marketplace before t_0 to see whether there is a statistical difference between the baseline projections and actual transactions (see Table 2). As we conjectured, no significant difference was found between the projections and actual transactions. This result indirectly shows the robustness of our model.

In Table 3, we compare the actual values of the *Number of Unique Customers*, *Number* (and *Size*) *of Orders*, *Cancellations*, *Returns* and *Exchanges* with their baselines forecasted using the VARX model for the adopter group. In contrast to the non-adopter group, most variables show significant differences before and after the mobile channel introduction. Specifically, the *Number of Orders*, *Number of Cancellations Before Payments*, *Number of Exchanges*, and *Number of Returns* increased significantly after the mobile channel introduction, while the *Size of Orders*, *Size of Cancellations Before Payments*, *Size of Cancellations After Payments*, *Size of Exchanges*, *Size of Returns*, and *Number of Cancellations After Payments* decreased. Note that merging the two cancellation categories leads to a net increase in the *Number of Cancellations* and a net decrease in the *Size of Cancellations*. In sum, the number of transactions increased, while the size of transactions decreased.

Table 2. Baseline Projections and Actual Transactions for the Non-Adopter Group

Variable		Baseline	Actual Post-Introduction	Increase / Decrease
Number of Unique Customers	Number	528.8 (8.4)	524.3 (7.8)	-
Order	Number	1,303.1 (20.3)	1,318.3 (22.5)	-
	Size	41,063.6 (435.6)	40,580.3 (672.1)	-
Cancellation Before Payment	Number	33.3 (0.4)	33.4 (0.8)	-
	Size	32,405.2 (364.7)	32,624.7 (1,070.9)	-
Cancellation After Payment	Number	62.4 (1.2)	62.1 (0.9)	-
	Size	66,063.5 (569.5)	66,290.7 (1,866.7)	-
Exchange	Number	5.0 (0.1)	4.9 (0.2)	-
	Size	34,466.6 (283.7)	36,544.3 (2,257.3)	-
Return	Number	20.0 (0.3)	19.8 (0.5)	-
	Size	50,884.2 (571.2)	53,429.3 (2,444.9)	-

- *Insignificant difference*, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The increase in *Numbers* clearly indicates that the use of the mobile channel triggered more transactions in the online channel. The *ubiquitous access capability* of the mobile channel could allow adopters to access the e-marketplace more and could consequently spark their interest in products. The products that are not time-critical and that need more extensive search will steer the customers to the online channel, which has *extensive information search capability*. The increase in the number of orders causes subsequent increases in the number of cancellations, exchanges, and returns.

Possible explanations for the decrease in *Sizes* are as follows. First, consumers' increased search due to lower search costs after the mobile channel introduction may have helped them find sellers offering lower prices. Second, triggering by the mobile channel might be associated with relatively less expensive or discounted products. Third, the mere dispersion of transactions over two channels could be the reason. This refers to the case when product *A* is purchased online and product *B* is purchased on the mobile channel, whereas both product *A* and product *B* might be purchased online had the mobile channel not been introduced.

Table 3. Baseline Projections and Actual Transactions for the Adopter Group

Variable		Channel	Baseline	Actual Post-Introduction	Increase (↑) / Decrease (↓)
Unique Customers	Number	Online	414.0 (5.2)	422.9 (5.7)	Not Sig.
		Mobile	N/A	76.0 (3.3)	
Order	Number	Online	826.6 (12.4)	1,024.6 (14.2)	↑24.0%***
		Mobile	N/A	120.4 (5.8)	
	Size	Online	32,270.6 (194.6)	29,899.5 (340.3)	↓7.4%***
		Mobile	N/A	26,038.4 (1,065.0)	
Cancellation Before Payment	Number	Online	35.6 (1.0)	63.2 (1.3)	↑77.4%***
		Mobile	N/A	10.2 (0.6)	
	Size	Online	61,922.3 (2,285.7)	40,071.5 (3,874.2)	↓35.3%***
		Mobile	N/A	39,411.3 (3,425.5)	
Cancellation After Payment	Number	Online	57.3 (0.6)	53.6 (0.9)	↓6.4%***
		Mobile	N/A	5.3 (0.3)	
	Size	Online	71,922.1 (849.5)	54,274.3 (1,349.1)	↓24.5%***
		Mobile	N/A	39,356.0 (1,918.9)	
Exchange	Number	Online	2.7 (0.1)	4.0 (0.15)	↑45.6%***
		Mobile	N/A	0.3 (0.0)	
	Size	Online	70,244.4 (1,397.6)	39,403.7 (2,576.6)	↓43.9%***
		Mobile	N/A	31,498.4 (1,385.2)	
Return	Number	Online	9.7 (0.3)	15,04 (0.4)	↑54.3%***
		Mobile	N/A	1.2 (0.1)	
	Size	Online	79,241.2 (2,049.2)	41,035.1 (1,778.2)	↓48.2%***
		Mobile	N/A	35,090.5 (2,193.2)	

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p< 0.001$

The presence of both the positive effect (an increase in the number) and the negative effect (a decrease in the size) makes it hard to assess the overall impact of the mobile channel introduction on existing customers. However, the effect from the increase in the *Numbers* turned out to dominate the effect from the decrease in the *Sizes*. Taking all revenue components into account, we found that the mobile channel introduction increases the revenue from adopters by 25.5%. Considering the fact that the m-commerce adoption rate for the e-marketplace is roughly 10%, the increase in total revenue due to the mobile channel introduction is estimated to be approximately 2.5%.

The rationale behind the triggering effect is that mobile channel usage triggers online channel usage only for those products that are not time-sensitive and that require extensive search. Thus, we next examine the impact of the mobile channel introduction in different product categories.

Impacts of Mobile Channel in Different Product Categories

We selected several categories available in the e-marketplace that correspond to the four quadrants based on time-criticality and information intensity (see Figure 3), both of which are relevant to the triggering effect by the mobile channel. First, Coupons and Tickets are assigned in Quadrant I, since they require relatively less information search, but are highly time-critical. An example is a discount coupon from Burger King, which is normally purchased when we are either on our way to the restaurant or on the spot. Since the product is already well-known to us and only a few officially designated sellers for the coupon sales are available in the market, additional extensive search on the coupon is not necessary. Another example is a concert ticket, which needs to be reserved early for a good seat. Early reservations also mean that we already know the concert-performer very well beforehand. Second, Baby Wipes, Diapers, Tissues, Confectionaries, Detergents and Storage are classified into Quadrant III. These are everyday products that are, by and large, well-known to us. Furthermore, their “physical” nature requires a certain amount of time to be delivered after purchase. In that sense, they are neither products for time-sensitive transactions nor products for extensive information search. Third, TVs, Fridges, Furniture, Laundry Machines, Dish Washers and Air Conditioners are classified into Quadrant IV. Assessing the value of the products in these categories require extensive search for both product attributes (e.g., technological functions and design), and service attributes (e.g., warranty conditions). As for Quadrant II, we found no available product categories for which the transaction is time-critical, but an extensive information search is required.

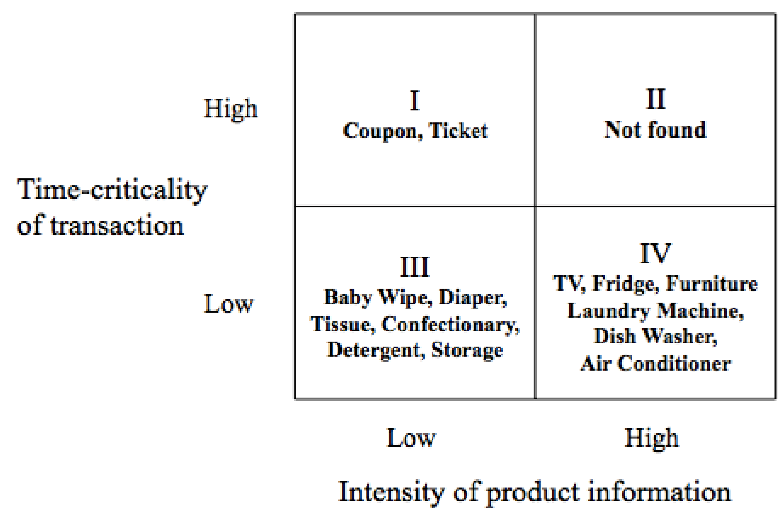

Figure 3. Classification on Product Categories

As mentioned above, the mobile channel – product fit in Quadrant I is the highest, while the fit in Quadrant IV is the lowest. Quadrant II and Quadrant III are in between. Online sales of the products in Quadrant I would be cannibalized by the mobile channel addition because the two capabilities of the mobile channel, ubiquitous access capability and limited information search capability, can substitute for the corresponding capabilities of the online channel. On the other hand, the high mobile channel – product fit would generate demand in the mobile channel. Furthermore, extensive search for products by customers would lead to a reduction in *Sizes*. Online sales of products in Quadrant IV would be minimally affected by the mobile channel addition due to the low mobile channel – product fit. Mobile sales in Quadrant IV would also be marginal. The impact on Sizes would be relatively low. Products in Quadrant III would be in between.

The results in Table 4, which compare between the baseline projections and actual transactions for each quadrant, partially support our early predictions. First, we found evidence of cannibalization of the online channel and demand generation by the mobile channel in Quadrant I. The demand for Coupons and Tickets in the online channel dropped by 6.5% after the introduction of the mobile channel. Ubiquitous access capability and limited information search capability of the mobile channel make it compatible with Quadrant I, and more or less substitute the demand of the online channel. However, an additionally large demand from the mobile channel has more than offset the cannibalization of the online channel, and has resulted in a 22.1% overall demand increase. Meanwhile, against our prediction, the average order size has also increased substantially in Quadrant I. One possible explanation is that customers' needs for coupons (or tickets) have greatly increased with the mobile channel addition, and they have started to transact multiple coupons at a time, or high-priced coupons.[5]

Table 4. Baseline Projections and Actual Transactions across Quadrants

Variable	Channel	Quadrant I (Coupons, Tickets)		Quadrant III (Baby Wipes, Diapers, Tissues, Confectionaries, Detergents, Storage)		Quadrant IV (TVs, Fridges, Furniture, Laundry Machines, Dish Washers, Air Conditioners)	
		Baseline	Actual	Baseline	Actual	Baseline	Actual
Number of Orders	Online	61.1 (1.7)	57.1 (1.3)	96.8 (2.5)	129.9 (2.6)	37.1 (0.8)	42.9 (0.8)
		↓6.5%$^{+}$		↑34.1%***		↑15.4%***	
	Mobile	NA	17.5 (0.4)	NA	13.8 (0.4)	NA	4.5 (0.1)
Size of Orders	Online	5,257.2 (303.6)	16,237.3 (317.1)	27,895.7 (219.3)	22,891.2 (217.4)	131,082.5 (2,064.3)	92,265.3 (2,275.1)
		↑208.9%***		↓17.9%***		↓29.6%***	
	Mobile	NA	15,621.5 (269.5)	NA	22,878.0 (201.1)	NA	88,395.5 (2,023.9)

$^{+}p<0.10$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p< 0.001$

In Quadrant III, we found a triggering effect in the online channel and demand generation in the mobile channel. Demand in the online channel is largely boosted (increased by 34.1%) by the introduction of the mobile channel. This increase is larger than the average increase for all product categories (24.0% in Table 3). However, the average order size has decreased by 17.9%, which means that there is order dispersion between the channels, which is consistent with the full sample result. The mobile channel itself also generated a substantial demand (about 10% of online demand).

In Quadrant IV, we found a minimal effect in both the online and mobile channels in Quadrant IV. A low mobile channel – product fit impedes searching in the mobile channel, and minimizes the possibility of channel synergy or cannibalization. The mobile channel introduction triggered an increase in online sales by 15.4%, which is less than the average of all product categories. The average order size decreased by 29.6%, which is consistent with the full sample result. Newly generated demand from the mobile channel was also the smallest among the quadrants.

Conclusion

Our data and analyses resulted in several interesting findings. First, overall we find that the mobile channel does not cannibalize, but rather enhances the traditional online channel. By separating the adopters and non-adopters of the mobile channel, we further find that this impact was observed only among the adopters of the mobile channel; the

[5] The substantial increase in order size might be due to a structural change in the Coupon or Ticket category after the mobile channel addition. Two possible changes might be possible: the existing coupon-issuers started to issue new high-priced coupons to meet the demand increase with the mobile channel addition, or new high-priced coupon-issuers entered the market after the mobile channel addition. We are currently looking into both possibilities.

introduction of the mobile channel had no impact on the non-adopters. In particular, the introduction of the mobile channel significantly increased the number of orders in the online channel while reducing the size of the orders somewhat, thereby leading to an overall increase in the revenue from the online channel. By accounting for the additional demand generated by the mobile channel, we estimate the overall revenue increase due to the introduction of the mobile channel to be 2.5%. More importantly, we find that the impact of the mobile channel depends on two product characteristics – time-criticality and information intensity – which are directly related to the capabilities of the mobile channel. Our results suggest that for products with high time-criticality and low information-intensity, the mobile channel cannibalizes the online channel, although the net impact of the mobile channel on the total revenue is positive because of its large demand generation effects. This implies that consumers are most likely to use the mobile channel as a substitute for the online channel concerning those products whose characteristics fit the mobile channel's capabilities the most. Regarding products with low time-criticality, however, we find a complementary impact of the mobile channel on the online channel, and this impact is greater in products with high information-intensity. This suggests that for products incompatible with the mobile channel's capabilities, consumers tend to use the mobile channel as a convenient information channel, which can in turn trigger online purchases.

This study makes several important research contributions. First, to the best of our knowledge, this is the first study that examines the impact of introducing a mobile channel on the existing online channel and a firm's revenue. Although there have been a few studies on the mobile channel, they have mostly focused on its unique characteristics and differences from the online channel (e.g., Ghose et al. 2012). We contribute to this nascent literature by empirically estimating the cross-channel and performance impacts of the mobile channel. Second, by showing that the impact of the mobile channel varies depending on the fit between the product characteristics and the capabilities of the mobile channel, we provide new insights into the interplay between product characteristics and channel capabilities, a topic that has not received much attention in the literature. Third, by effectively controlling for the entry of new customers and the exit of existing customers, which can significantly confound the analysis, we could estimate the impact of introducing a new channel more accurately, compared to prior studies. Fourth, we introduce the IS community to a novel empirical method, namely, a multivariate baseline analysis based on vector auto-regression with exogenous variables (VARX), which has recently been used in marketing. We believe that this method can be useful in evaluating the impact of IT-related events on various performance measures.

In addition, this study provides important managerial implications. First, given that adding the mobile channel increases not only revenue from the online channel, but also the total firm revenue, firms should introduce a mobile channel without worrying about its cannibalization effect. By not launching the mobile channel, firms will miss the opportunity to capitalize on the mobile channel's potential to enhance the online channel and generate additional demand. Second, when firms launch a mobile channel, they need to be aggressive in having their customers adopt the new channel so that they can fully realize the revenue-generating potential of the mobile channel. Finally, our results suggest that firms need to recognize the differences across products in terms of time-criticality and information-intensity when they develop their multi-channel strategy.

References

Abraham, M.M. and L.M., Lodish. 1993. "An Implemented System for Improving Promotion Productivity Using Store Scanner Data," *Marketing Science* (12:3), pp. 248-269.

Afuah, A. and C. L. Tucci. 2002. *Internet Business Models and Strategies: Text and Cases*, McGraw-Hill/Irwin (2e).

Avery, J., T. J. Steenburgh, J. Deighton, and M. Caravella. 2012. "Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities Over Time," *Journal of Marketing* (76:2), pp. 96-111.

Biyalogorsky, E. and P. Naik. 2003. "Clicks and Mortar: The Effect of Online Activities on Offline Sales," *Marketing Letters* (14:1), pp. 21–32.

Brewer-Hay, R. 2012. "John Donahoe: eBay Mobile GMV will surpass $8 Billion in 2012," available at: http://ebayinkblog.com/2012/01/11/2012_mobile_projections/

Brynjolfsson, E. and M. Smith. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science* (46:4), pp. 563-585.

Cisco. 2011. "Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2011–2016," available at: http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537/ns705/ns827/white_paper_c11-520862.pdf

Clemons, E., I.-H. Hann, and L. Hitt. 2002. "Price Dispersion and Differentiation in Online Travel: An Empirical Investigation," *Management Science* (48:4), pp. 534-549.

Danaher, B., S. Dhanasobhon, M. D. Smith, and R. Telang. 2010. "Converting Pirates Without Cannibalizing Purchasers: The Impact of Digital Distribution on Physical Sales and Internet Piracy," *Marketing Science* (29:6), pp. 1138-1151.

Deleersnyder, B., I. Geyskens, K. Gielens, and M. G. Dekimpe. 2002. "How Cannibalistic Is the Internet Channel? A Study of the Newspaper Industry in the United Kingdom and The Netherlands," *International Journal of Research in Marketing* (19:4), pp. 337–348.

Dekimpe, M.G., and D.M. Hanssens. 1999. "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research* (36:4), pp. 397-412.

Duchnicky, R. L., and P. A. Kolers. 1983. "Readability of Text Scrolled on Visual Display Terminals as a Function of Window Size," *Human Factors* (25:6), pp. 683-892.

Gartner. 2012. "Gartner Says Worldwide Mobile Payment Transaction Value to Surpass $171.5 Billion," available at: http://www.gartner.com/it/page.jsp?id=2028315.

Ghose, A., A. Goldfarb, and S. Han. 2012. "How is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research*, forthcoming.

Google/IPSOS OTX. 2011. "The Mobile Movement: Understanding Smartphone Users," available at: http://www.gstatic.com/ads/research/en/2011_TheMobileMovement.pdf.

Grieger, M. 2003. "Electronic Marketplaces: A Literature Review and a Call for Supply Chain Management Research," *European Journal of Operational Research* (144:2), pp. 280-294.

Huang, P., N. H. Lurie, and S. Mitra. 2009. "Searching for Experience on the Web: An Empirical Examination of Consumer Behavior for Search and Experience Goods," *Journal of Marketing* (73:1), pp. 55-69.

Jones, M., Marsden, G., Mohd-Nasir, N., Boone, K., and Buchanan, G. 1999. "Improving Web Interaction in Small Screen Displays," in *Proceedings of the 8th World Wide Web Conference*, Toronto, May 11-14, pp. 51-59.

Kuruzovich, J., S. Viswanathan, R. Agarwal, S. Gosain, and S. Weitzman. 2008. "Marketspace or Marketplace? Online Information Search and Channel Outcomes in Auto Retailing," *Information Systems Research* (19:2), pp. 182-201.

Mulpuru, S. 2011. "The Mobile Commerce Train: Coming But Not Here Yet," available at: http://blogs.forrester.com/sucharita_mulpuru/11-06-17-the_mobile_commerce_train_coming_but_not_here_yet.

Neslin, S. and V. Shankar. 2009. "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," *Journal of Interactive Marketing* (23:1), pp. 70-81.

Pauwels, K., J. Silva-Risso, S. Srinivasan and D. M. Hanssens. 2004. "New Products, Sales Promotions and Firm Value: The Case of the Automobile Industry," *Journal of Marketing* (68:4) pp. 142-156.

Pauwels, K. and S. A. Neslin. 2011. "Building with Bricks and Mortar: The Revenue Impact of Opening Physical Stores in a Multichannel Environment," Working paper, Tuck School of Business, Dartmouth College.

Shop.org/Forrester Research. 2011. "Retailers Increasing Mobile and Social Efforts: According to Shop.org/Forrester Survey," available at: http://www.shop.org/c/journal_articles/view_article_content?groupId=1&articleId=1356&version=1.0.

Stigler, G. J. 1961. "The Economics of Information," *Journal of Political Economy* (69:3), pp. 213–25.

Venkatesh, V., V. Ramesh, and A. P. Massey. 2003. "Understanding Usability in Mobile Commerce," *Communications of the ACM* (46:12), pp. 53-56.

Venkatesh, V. and V. Ramesh. 2006. "Web and Wireless Site Usability: Understanding Differences and Modeling Use," *MIS Quarterly* (30:1), pp. 181-206.

Verhoef, P. C., S. A. Neslin, and B. Vroomen. 2007. "Multi-channel Customer Management: Understanding the Research Shopper Phenomenon," *International Journal of Research in Marketing* (24:2), pp. 129–148.