Channel Capabilities, Product Characteristics, and the Impacts of Mobile Channel Introduction

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ABSTRACT: Drawing on the notion of channel capability, we develop a theoretical framework for understanding the interactions between mobile and traditional online channels for products with different characteristics. Specifically, we identify two channel capabilities—access and search capabilities—that differentiate mobile and online channels, and two product characteristics that are directly related to the channel capabilities—time criticality and information intensity. Based on this framework, we generate a set of predictions on the differential effects of mobile channel introduction across different product categories. We test the predictions by applying a counterfactual analysis based on vector autoregression to a large panel data set from a leading e-market in Korea that covers a 28-month period and contains all of the transactions made through the online and mobile channels before and after the mobile channel introduction. Consistent with our theoretical predictions, our results suggest that the performance impact of the mobile channel depends on the two product characteristics and the resulting product-channel fit. We discuss implications for theory and multichannel strategy.

KEY WORDS AND PHRASES: counterfactual analysis, e-commerce, mobile commerce, multichannel strategy, multivariate baseline analysis, substitute and complement, times series, vector autoregression.

The explosive penetration of mobile devices, together with the growth of mobile networks, is one of the most prominent trends in today’s information technology (IT). According to a recent study by Cisco [9], the number of mobile devices will exceed the world’s population in 2013, and mobile data traffic will increase 13-fold between 2012 and 2017. With the prevalence of mobile devices and networks, the mobile channel is rapidly emerging as a new commerce venue. Global mobile transactions are expected to reach $617 billion, with 448 million users by 2016 [18].

Adding mobile channels to traditional e-commerce channels (online channels hereafter) based on the fixed Internet is a crucial decision for firms. According to a survey by Shop.org/Forrester Research [48], 91 percent of online retailers in the United States have a mobile strategy in place or in development. Forty-eight percent of the retailers surveyed report having a mobile Web site, 35 percent have deployed an iPhone app, and 15 percent offer an Android app. Without systematic multichannel strategies, the implementation of mobile channels might result in merely another competitive necessity, as in the case of bank automatic teller machines [11]. In contrast, a well-developed multichannel strategy can improve firm performance (e.g., [30, 52]) while limiting any negative consequences, such as channel conflict [3, 22]. In order to craft an effective multichannel strategy that includes a new mobile channel, it is crucial for firms to assess the performance effects of adding the new channel on their existing online channel in terms of cross-channel cannibalization versus synergy [42].
It is not clear, however, how introducing a mobile channel affects the existing online channels of individual firms. On the one hand, the introduction of a mobile channel can provide an alternative channel for consumers to buy products that they would otherwise buy through an existing online channel, leading to substitution of the online channel. On the other hand, a mobile channel can enhance consumers’ information search ability by allowing consumers to search for product information anywhere, anytime they want, which in turn can trigger additional purchases on the online channel.

Moreover, given that the mobile channel may not fit all types of products, understanding the impact of a mobile channel introduction on different product categories is important. For example, tickets for entertainment or sporting events have been suggested as well-suited products for the mobile channel [39], whereas big-ticket items such as jewelry are not easily transacted on mobile devices because customers require more research [38].

There have been a number of empirical studies on the performance effects of introducing a new channel on the existing channel in the context of newspapers and magazines [13, 20, 51], music [7], DVDs [12], as well as general consumer products [4, 45]. These studies have focused on the interactions between online and offline channels, and their findings suggest that the impact of a new channel introduction on an existing channel may differ across different product categories. For example, while previous studies on newspapers and magazines have mostly found a substitution effect in the case of online channel introduction [20, 31, 51], the effect was not significant for music and DVDs [7, 12], although the channel composition and the order of the channel introductions were identical. In addition, there is relatively abundant theoretical work on multichannel strategies [5, 8, 17, 49, 56].

A few studies have examined the impact of introducing a mobile channel as a service channel. Most notably, Jung [27] examined the impact of smartphone adoption on fixed broadband Internet service and cable television service subscriptions, and found no substitution effect. Jung and Lee [28] explored the interactions between online and mobile channels in banking services and found that mobile banking complements online banking.

Although these studies provide useful insights into the interactions among different channels, there are important gaps in the literature. First, prior studies have not examined the impact of introducing a mobile channel as a commerce channel. Most studies have analyzed the interactions among the offline, online, and catalog channels, leaving out the mobile channel. Those few studies that examined the impact of mobile channel have focused on contexts in which the mobile channel is used as a service channel (i.e., Internet and banking services). As a result, there is little guidance that can be offered for e-commerce firms when they are considering adding a mobile channel to their online channels. Second, the results of prior work have limited implications for the differential effects of channel introduction across product categories because their analyses are based on a single product category [7] or data aggregated across products [4, 45]. Most importantly, prior studies do not provide theoretical perspectives that help determine the fit between a channel and a product,
and generate predictions on the differential effects of a channel introduction across different product categories.

To fill these gaps and enrich our understanding of the impact of a mobile channel introduction in a multichannel environment, we address the following research questions:

**RQ1:** What theoretical perspective can guide us in examining the impact of a new mobile channel on the existing online channel?

**RQ2:** How does the impact of introducing a mobile channel differ, depending on product characteristics?

**RQ3:** How should we determine the fit between a channel and a product?

In order to address these questions, we begin by theorizing about how the mobile channel introduction would influence multichannel performances across products with different characteristics. We draw on the notion of *channel capabilities* proposed by Avery et al. [4] and extend their framework by relating the capabilities of online and mobile channels with product characteristics in order to examine the differential performance impact across product categories. Building on prior IS and marketing literature, we identify two contrasting capabilities of online and mobile channels in terms of *access* and *search*, and link these capabilities to two product characteristics: the *time-criticality of transactions* and the *intensity of product information*.

Then, we test our predictions by applying a counterfactual analysis based on *vector autoregression with exogenous variables* (VARX) to a large panel data set from a leading Korean e-market that initially offered an online channel only and introduced a mobile channel later. The data set includes all the transactions through both the online and mobile channels by a sample of customers before and after the introduction of the mobile channel; therefore, we can predict the postmobile introduction transactions in the online channel that would have resulted without the mobile channel introduction and compare these predicted transactions with the actual ones.

We find that for products with high time criticality and low information intensity, the mobile channel substitutes for the online channel significantly. In contrast, regarding products with high time criticality and high information intensity, we find a strong synergy between the online and mobile channels. For products with low time criticality and low information intensity, the mobile channel increases the online channel transactions while generating substantial transactions of its own. Finally, for products with low time criticality and high information intensity, we find a moderate complementary effect of the mobile channel. Taken together, our results suggest that the performance impact of the mobile channel depends crucially on the product characteristics and resulting product-channel fit.

Subsequently, we develop our theoretical framework and predictions, discuss the research methods and data, and present the findings of our study. We conclude with a discussion of contributions, implications, and limitations.
Theoretical Framework

Channel Capabilities

Avery et al. define a channel capability as “an enabling characteristic of a channel that allows consumers to accomplish their shopping goals” [4, pp. 96–97]. They suggest that each capability of a new channel can be evaluated based on whether this capability substitutes for or complements the capabilities of the preexisting channels. When the new channel has a substitutive capability, it will cannibalize demand in the preexisting channel. On the contrary, when the new channel has a complementary capability, it will create additional demand for the preexisting channel.

While this channel capability framework is clear and convincing, it is difficult to apply when a new channel has many capabilities that are different from those of the preexisting channel. In the case of an interaction between mobile and online channels, however, the task is simpler because the number of relevant capabilities is limited, as described below.

Access and Search Capabilities of the 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. There are, nonetheless, distinct capabilities between the online and mobile channels that result from inherent differences between the fixed Internet and the mobile Internet.

Prior studies suggest that there are two features that distinguish the mobile and online channels: ubiquity and usability [10, 34, 54]. Ubiquity is one of the most prominent advantages of mobile channels over traditional online channels, allowing instant Internet access. However, mobile channels have a disadvantage in usability due to constraints in mobile devices (e.g., small screens) and mobile networks (e.g., low bandwidth). Taken together, the mobile channel can be characterized as easier to access, but harder to browse, compared with the online channel.

From ubiquity and usability, we derive two capabilities that distinguish the mobile and online channels: access and search capabilities. First, mobile devices are not fixed to a location [21], and consumers can access mobile channels wherever and whenever they want. This is a critical capability in favor of mobile channels, which we call ubiquitous access capability, versus the constrained access capability of the online channel. While e-commerce based on the fixed Internet can overcome geographic distance, enabling buyers to access remote sellers [1], buyers’ locations are fixed to places that have PCs (personal computers) and Internet connections. In contrast, mobile channels are not subject to such a constraint, thereby supporting time-critical activities [55] and facilitating immediate transactions.
Second, because of the small screens and low usability of mobile devices, information search through mobile channels is substantially limited, compared to online channels. Such a limitation may also hamper longer and more complex uses of mobile channels, possibly increasing search costs [6, 16, 21]. Therefore, e-commerce firms usually offer their mobile Web sites or apps in more streamlined forms, compared to regular Web sites. In summary, mobile and online channels are essentially different in their information search capabilities, which we refer to as an extensive information search capability for online channels and a limited information search capability for mobile channels.

Channel Capabilities, Product Characteristics, and Mobile Channel Impacts

Given that access and search capabilities can distinguish the two types of channels, consumers’ use of the channels for search and purchase of a product would be primarily determined by the fit between the channel and the product, specifically, the channel capabilities and the product characteristics. In order to evaluate the product-channel fit, we define two product characteristics that are directly related to the two capabilities: the time criticality of transactions and the intensity of product information.

The time criticality of transactions for a product is related to the change in the buyer’s utility from the product, depending on the time of purchase [19, 33]. Some products are characterized by strong time constraints for purchase (and therefore consumption), while others are not. Products for which demand is concentrated around the time of specific holidays (e.g., Christmas, Thanksgiving, the Lunar New Year, and Easter) are highly time-critical. For example, the value of Christmas gifts for children declines sharply after Christmas. Products that consumers commonly buy for specific personal events (e.g., anniversary, birthday, and vacation) are also time critical. For example, everyone wants a travel package that matches his or her vacation schedule. Products featuring high seasonal demand that lasts for a short time period are also time critical as well. Demand for barbecue products is highest in the United States just before July 4, with a very sharp spike and then drop off, for example [40]. Time pressure limits purchase deliberation [46]. Furthermore, people value proximity and swiftness to fulfill purchases in their store choices for time-constrained purchases [53]. Therefore, time criticality is expected to interact with the access capabilities of the channels to determine consumers’ channel choices.

Product information intensity refers to the amount of information a consumer needs to process before making purchase decisions [44, 50]. While a variety of types of information are available to consumers, including product descriptions, customer reviews, price information, and delivery and return policies, all of the information is not critical to all product categories that consumers evaluate. Some product categories (e.g., home furniture and cameras) involve extensive searches in terms of the number of pages viewed and the total time spent on search, whereas other categories (e.g., health and beauty products) entail much less extensive searches [26]. Other things being equal, information-intensive products are likely to lead to more in-depth searches
and broader searches for product information. Given the different level of information search capabilities between online and mobile channels, the information intensity of a product may affect which channel consumers prefer to use.

Based on the values (high and low) of the two dimensions, we came up with four distinct quadrants, as shown in Figure 1. To be able to make predictions regarding the impact of adding a mobile channel, we first evaluated the product-channel fit in each quadrant. Because the mobile channel can be an effective channel for both time-critical and non-time-critical transactions, as long as its limited information search capability does not impede the transactions on the channel, the fit between a product and the mobile channel is determined solely by the product’s information intensity: for high (low) information-intensity products, the fit with the mobile channel is low (high). By the same token, given that the online channel is effective for both high and low information-intensity products, as long as its constrained access capability does not become an obstacle to transactions on the channel, the fit between a product and the online channel is determined solely by time criticality: the fit with the online channel is high (low) for low (high) time-criticality products. Figure 1 summarizes the relative fit between products and the two types of channels in each quadrant.

Products in Quadrant I have a low (high) fit with the online (mobile) channel. The mobile channel can provide an excellent access medium for them, thanks to its ubiquitous access capability. In addition, a low level of information intensity indicates that the limited search capability of the mobile channel will not impede transactions of these products. Thus, the mobile channel can be an effective substitute for the online channel. In addition, the ubiquitous access capability of the mobile channel can entail new demand. For instance, a consumer on the move may realize that today is his wife’s birthday and may search for a flower delivery service and purchase flowers immediately using his smartphone. Therefore, we expect that the major impact of the mobile channel will be substitution of the online channel, thereby resulting in a reduction in online transactions. At the same time, we expect the mobile channel to generate a substantial new demand of its own.
For products in Quadrant II, each channel has its own weakness, resulting in a low fit for both channels. Thus, the mobile channel is not an effective substitute for the online channel. Taken together, however, the two channels can complement each other very well: the mobile channel provides ubiquitous access capability, while the online channel provides extensive search capability. For instance, a consumer may find a nice travel package for his or her family vacation while browsing the mobile Web during the day and then search for additional information and purchase the package on his or her PC in the evening. Given that consumers are likely to purchase a product when they have enough information about it, we believe that most of the channel synergy will be realized on the online channel, and new demand generation in the mobile channel will be minimal (due to the low product-channel fit). Therefore, we expect the mobile channel to increase the demand on the online channel and to generate a minimal new demand of its own.

Products in Quadrant III have a high fit with both channels. For instance, the utility of paper towels is not likely to change over time. Furthermore, few consumers search and process a large amount of information to buy the product. Because the mobile channel provides another effective channel in addition to the online channel, we believe that it will generate a significant new demand, although this effect will be smaller than that in Quadrant I due to low time criticality. Regarding the cross-channel interactions, the mobile channel may have both substitutive and complementary effects on the online channel. On the one hand, because the mobile channel can be as effective a medium as the online channel, consumers can use the former for purchases instead of the latter. On the other hand, consumers may search for product information on their mobile devices and may purchase the product later on their PC because the transaction is not time critical, thereby triggering additional demand on the online channel. Although we do not know which effect will be dominant, given that part of the new demand generated on the mobile channel will be realized as transactions on the online channel, we expect the net effect of the mobile channel on the online channel to be an increase in the online demand.

Finally, in Quadrant IV, products fit perfectly with the online channel; however, the mobile channel is not effective at all. Due to the low time criticality, the ubiquitous access capability of the mobile channel would be less valued here. Furthermore, a high level of information intensity indicates that an information search through the mobile channel is not likely to be sufficient in making purchase decisions (e.g., the purchase of a laptop usually involves evaluations of various performance attributes, design, and others’ reviews). Given that the mobile channel is a poor fit for these products, we expect that the mobile channel’s effect on the online channel, as well as its own demand generation effect, would be minimal.

Methodology

To analyze the effect of the mobile channel introduction on the preexisting online channel, we need a counterfactual analysis to compare the performance variables (e.g., the number of orders, the size of orders, revenue) with and without the mobile channel.
introduction. Since we can only observe the outcome for the mobile channel introduction, the essence of the analysis is to assess the potential outcome without the mobile channel introduction. To this end, we employ a multivariate baseline analysis based on vector autoregression with exogenous variables (VARX).

VARX is an appropriate method in our study context. First, it can easily capture complex feedback effects where several endogenous variables affect each other over time. In our study, several endogenous variables, such as the number (and size) of orders, the number (and size) of cancellations, and the number (and size) of returns are expected to affect one another over time. Second, VARX can incorporate exogenous variables that can influence endogenous variables in the model, thereby extending the traditional VAR model, which can typically account for endogenous variables only. This feature is important in our study because generating accurate predictions for several performance variables is critical, and the predictions can be influenced by exogenous variables, such as market size and market share of the e-market. Third, VARX can take into account possible biases from autocorrelations and reverse causality [37]. Last, the forecasts obtained by VARX are known to be better than those obtained from the more complex simultaneous equations models in many cases [24, 32], which serves our purpose of producing potential outcomes well.

We next identify variables that are relevant to the market outcome. **Number (and Size) of Orders, Cancellations, Returns, and Exchanges** are the focal variables. Number of Orders and Size of Orders are the daily number of unique orders and the daily average of order sizes in terms of the amount. Note that the sum of all the order sizes may not imply the revenue, since an order might end up as an order cancellation, product exchange, or product return. Cancellations (before and after payments), Returns, and Exchanges are the daily number of order cancellations before and after payments, product returns, and product exchanges, respectively.

Then, we identify a number of control variables that can either endogenously or exogenously influence the focal variables: **Market Size** (of the total Korean e-commerce sector), **Level of Market Competition**, **Market Share** (of the e-market), **Number of Promotions**, and **Seasonal Dummies** (daily). We controlled for both the Market Size and Market Share of the e-market to account for the growth of the entire market size and the share of the focal e-market—failure to control for these variables would underestimate our baseline, thereby overstating the impact of the mobile channel introduction. Both Market Size and Market Share are based on the transaction volumes in terms of price. We obtained the monthly market size from Statistics Korea and the yearly market share from the Fair Trade Commission Korea. Since we need daily data for these 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 the Level of Market Competition, as 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 percent of the Korea e-market sector. We control for the Number of Promotions, which is the number of promotions issued by the e-market during a day. Finally, we include six daily dummies in the model to control for day-specific effects.
We next employed a VARX model to extrapolate the endogenous variables into the postintroduction period. \(^4\) We modeled all of the outcome variables as endogenous. As a result, we ended up with ten endogenous variables. This resulted in the following estimation model:

\[
\begin{bmatrix}
NO_t \\
SO_t \\
NCA_t \\
SCA_t \\
NCB_t \\
SCB_t \\
NR_t \\
SR_t \\
NE_t \\
SE_t
\end{bmatrix} = 
\begin{bmatrix}
C_1 + \sum_{d=1}^{6} \chi_{1d} S_{dt} \\
C_2 + \sum_{d=1}^{6} \chi_{2d} S_{dt} \\
C_3 + \sum_{d=1}^{6} \chi_{3d} S_{dt} \\
C_4 + \sum_{d=1}^{6} \chi_{4d} S_{dt} \\
C_5 + \sum_{d=1}^{6} \chi_{5d} S_{dt} \\
C_6 + \sum_{d=1}^{6} \chi_{6d} S_{dt} \\
C_7 + \sum_{d=1}^{6} \chi_{7d} S_{dt} \\
C_8 + \sum_{d=1}^{6} \chi_{8d} S_{dt} \\
C_9 + \sum_{d=1}^{6} \chi_{9d} S_{dt} \\
C_{10} + \sum_{d=1}^{6} \chi_{10d} S_{dt}
\end{bmatrix} + \sum_{k=1}^{K} A_i^k \times NO_{t-k} + \sum_{k=1}^{K} A_i^k \times SO_{t-k} + \sum_{k=1}^{K} A_i^k \times NCA_{t-k} + \sum_{k=1}^{K} A_i^k \times SCA_{t-k} + \sum_{k=1}^{K} A_i^k \times NCB_{t-k} + \sum_{k=1}^{K} A_i^k \times SCB_{t-k} + \sum_{k=1}^{K} A_i^k \times NR_{t-k} + \sum_{k=1}^{K} A_i^k \times SR_{t-k} + \sum_{k=1}^{K} A_i^k \times NE_{t-k} + \sum_{k=1}^{K} A_i^k \times SE_{t-k} + \sum_{k=1}^{K} A_i^k \times MSZ_{t-k} + \sum_{k=1}^{K} A_i^k \times LMC_{t-k} + \sum_{k=1}^{K} A_i^k \times MS_{t-k} + \sum_{k=1}^{K} A_i^k \times NP_{t-k} + \sum_{k=1}^{K} A_i^k \times U_t,
\]

where \(NO_t = Number\ of\ Orders\) 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 \(t\); \(SCA_t = Size\ of\ Cancellations\ After\ Payments\) 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 \(t\); \(C_i = constant\ for\ the\ i-th\ equation\); \(S_{di} = 6\ daily\ seasonal\ dummies\ for\ period\ t\); \(\chi_{di} = \text{coefficient\ for\ } S_{di}\ \text{in\ the\ } i-th\ \text{equation}\); \(A_i^k = (10 \times 10)\ matrix\ of\ coefficients\ for\ endogenous\ variables\ for\ period\ } t – k; \(B_i = (10 \times 4)\ matrix\ of\ coefficients\ for\ exogenous\ variables\ for\ period\ t\); and \(U_t = (10 \times 1)\ vector\ of\ error\ terms\ for\ period\ t\).

The number of lags, \(K\), is determined by the Schwarz information criterion (SC) and the Akaike information criterion (AIC). Finally, the estimated VARX model extrapolates all of the endogenous variables into the postintroduction period, generating the baseline. The difference between the baseline value and the actual value on each outcome variable is examined by a pairwise \(t\)-test. Finally, the revenue without the mobile channel introduction can be computed and compared with the actual revenue in the postintroduction period.

**Data and Variables**

We obtained two large data sets from a major e-market in Korea that had initially provided an online channel only and launched a mobile channel later at the beginning of June 2010 \((t_i)\). Each data set covers the period from March 2009 \((t_i)\) to June 2011.
The impacts of mobile channel introduction and contains users’ transaction records, including orders, cancellations before and after payments, exchanges, and returns. The first data set contains a random sample of 30,000 users who did not adopt the mobile channel (the nonadopter group hereafter) until $t_2$ and their entire transaction records from $t_0$ to $t_2$. The second data set contains a random sample of 30,000 users who adopted the mobile channel before $t_1$ (the adopter group hereafter) and their entire record of transactions made through the online and mobile channels during the same period. Our data sets capture transactions before and after the introduction of the mobile channel ($t_1$), which gives us a nice opportunity to explore the impact of the mobile channel introduction in a quasieperimental setting.

Figure 2 shows the composition of our data sets. $t_0$ is the beginning of the time span of the data sets, $t_1$ is the time when the e-market launched the mobile channel, and $t_2$ is the end of the time span of the data sets. Note that there is no mobile transaction between $t_0$ and $t_1$ because the mobile channel was not available at that time.

Since we are primarily interested in examining the impact of the mobile channel’s introduction on the purchase behavior of existing customers, we used the second data set for our main analysis; we used the first data set to validate our baseline model. The transactions between $t_0$ and $t_1$ were used to derive the baselines for each data set. The baseline obtained from Data set 1 was compared with the actual outcome of the nonadopter group between $t_1$ and $t_2$ for model validation. The baseline obtained from Data set 2 was compared with the actual online and mobile transactions of the adopter group between $t_1$ and $t_2$ to estimate the effect of the mobile channel introduction.

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. Furthermore, newcomers’ purchase patterns may be different from those of existing consumers [4]. Fortunately, our data set allows us to focus on existing customers who had already joined the e-market before $t_0$ ($n_1 = 16,108$ for the nonadopter group, $n_2 = 12,239$ for the adopter group). The total numbers of transactions from the existing customers that were used for the model validation and effect estimation are 866,137 (Data set 1) and 685,003 (Data set 2), respectively. By removing the customers added between $t_0$ and $t_1$, we can tease out the effect of the mobile channel on the purchase behavior of the existing customers.
Table 1. Descriptive Statistics (Adopter Group)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Online channel before introduction</th>
<th>Online channel after introduction</th>
<th>Mobile channel after introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>Number of Orders</td>
<td>581.6</td>
<td>230.1</td>
<td>1,024.6</td>
</tr>
<tr>
<td>Size of Orders</td>
<td>31.0</td>
<td>12.3</td>
<td>26.9</td>
</tr>
</tbody>
</table>

Notes: SD = standard deviation. Size is in U.S. dollars (US$1 = 1,110.5 Korean won as of October 12, 2012).

Table 1 shows the descriptive statistics of Number of Orders and Size of Orders, our key endogenous variables, before and after the mobile channel introduction in the adopter sample. On average, approximately 582 (1,025) orders were made through the online channel every day before (after) the mobile channel introduction. Although it appears that there was a huge positive effect by the mobile channel introduction on the number of orders, we cannot conclude anything at the moment, since this increase may be due to either a fast upward trend of the number of orders or other factors that affected the number of orders and changed over time. Our baseline model, based on VARX, can effectively control for the effects of such factors. The daily average size of orders, however, decreased after the mobile channel introduction (from $31 to $27).

Results

Overall Impact of Mobile Channel Introduction

In estimating the VARX model for adopters, the optimal lag order for both the endogenous and exogenous variables was selected to be one, based on the SC and the AIC. We checked whether the endogenous variables are stationary or evolving by using the augmented Dickey–Fuller (ADF) test. As reported in Table 2, the ADF test results for all the variables are less than the critical value of –2.87, suggesting that we can reject the null hypothesis of a unit root at the 95 percent confidence level. This confirms that all the endogenous variables follow stationary processes. Next, we used the Granger causality test to see whether our endogenous variables can be treated as exogenous. For each endogenous variable in the model, the joint significance of the other lagged endogenous variables was tested with $\chi^2$ statistics. As reported in Table 2, the Granger causality test results indicate that all the variables in the model can be treated as endogenous. The VAR residual heteroskedasticity test indicate that we cannot reject the null hypothesis of homoskedasticity.

Table 3 compares the actual values of the Number (and Size) of Orders with their baselines forecasted using the VARX model for the adopter group. We analyzed the impact of the mobile channel introduction on the online channel by comparing the baseline with the postintroduction actual outcome. There are significant differences
before and after the mobile channel introduction. Specifically, the *Number of Orders* increased significantly after the mobile channel introduction while the *Size of Orders* decreased.

Given the presence of both the positive effect (an increase in the number) and the negative effect (a decrease in the size), we calculated the revenue to assess the overall impact of the mobile channel introduction on existing customers. The result indicates that the effect from the increase in the number of orders dominated the effect from the decrease in order size. Taking all the revenue components into account, we found that the mobile channel introduction increased the revenue from the adopter group by 18.4 percent.\(^5\)

**Mobile Channel Effects for Different Product Categories**

We selected several categories available in the e-market that correspond to the four quadrants in Figure 1, based on time criticality and information intensity. Four of the authors independently rated time criticality and information intensity for 56 product categories, based on the classification system used by the e-market. We used the criteria described earlier: three criteria for time criticality (how concentrated the demand for a given product category is around specific holidays, how related a given product category is with personal events, and how seasonal the demand is) and two criteria for information intensity (how deep a consumer is required to search for product information and how broad a consumer is required to search for product information).

When classifying the categories, four options were available for each dimension: Low, Medium, High, and Difficult-to-Classify. Since our framework addresses high or low levels of products in each dimension, we included Medium to filter out products that are intermediate in terms of either dimension. When a product category was marked as Difficult-to-Classify by anyone, then the category was removed from the

<table>
<thead>
<tr>
<th>Table 2. ADF and Granger Causality Tests for Endogenous Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unit root</strong></td>
</tr>
<tr>
<td>Number of Orders</td>
</tr>
<tr>
<td>Size of Orders</td>
</tr>
<tr>
<td>Number of Cancellations Before Payments</td>
</tr>
<tr>
<td>Size of Cancellations Before Payments</td>
</tr>
<tr>
<td>Number of Cancellations After Payments</td>
</tr>
<tr>
<td>Size of Cancellations After Payments</td>
</tr>
<tr>
<td>Number of Returns</td>
</tr>
<tr>
<td>Size of Returns</td>
</tr>
<tr>
<td>Number of Exchanges</td>
</tr>
<tr>
<td>Size of Exchanges</td>
</tr>
</tbody>
</table>

*Notes:* The critical value of the ADF test statistic at the 95 percent level is −2.87. The critical value of the test statistic for the Granger causality tests at the 95 percent level is 19.68.
list. Among the remaining 34 categories, we retained 24 categories that received at least 3 High ratings or 3 Low ratings. For each product category chosen, we examined its subcategories and excluded several subcategories that do not match each quadrant. For example, the Flowers category was initially selected as a candidate for Quadrant I (high time criticality and low information intensity). However, because the category included Horticultural Crops, which might not match the quadrant, as well as Flower Deliveries, which match the quadrant well, we removed Horticultural Crops, and renamed the category Flower Deliveries.

Coupons, Tickets, Flower Deliveries, Cake Deliveries, and Diapers were assigned to Quadrant I, since they require relatively less of an information search but are highly time critical. An example is a discount coupon from Burger King, which is normally purchased when people are either on their way to the restaurant or on the spot. Since the product is already well known to people, and only a few officially designated sellers of the coupon 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 people already know the performer well beforehand.

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Channel</th>
<th>Baseline</th>
<th>Actual postintroduction</th>
<th>Increase (↑)/decrease (↓) (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Orders</td>
<td>Online</td>
<td>827.6 (11.4)</td>
<td>1,024.6 (14.2)</td>
<td>↑ 23.8***</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>—</td>
<td>120.4 (5.8)</td>
<td></td>
</tr>
<tr>
<td>Size of Orders</td>
<td>Online</td>
<td>30.5 (0.2)</td>
<td>26.9 (0.3)</td>
<td>↓ 11.8***</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>—</td>
<td>23.5 (1.0)</td>
<td></td>
</tr>
<tr>
<td>Revenue</td>
<td>Online</td>
<td>21,015.7 (330.7)</td>
<td>22,199.0 (370.1)</td>
<td>↑ 5.6*</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>—</td>
<td>2,707.6 (141.2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>21,015.7 (330.7)</td>
<td>24,874.0 (440.4)</td>
<td>↑ 18.4***</td>
</tr>
</tbody>
</table>

Notes: Size is in U.S. dollars. Standard errors are in parentheses. In calculating the total revenue, we first calculated daily revenues separately by multiplying the number and size of orders, and took the average. A number of variables showed similar patterns. Number of Cancellations Before Payments, Number of Exchanges, and Number of Returns increased significantly after the mobile channel introduction, while the Size of Cancellations Before Payments, Size of Cancellations After Payments, Size of Exchanges, Size of Returns, and Number of Cancellations After Payments decreased. Merging the two cancellation categories leads to a net increase in the Number of Cancellations and a net decrease in the Size of Cancellations. * $p < 0.05; ** p < 0.01; *** p < 0.001.
Event/Party Products, Telecommunications Services, Travel Packages, and Presents were assigned to Quadrant II. These items are both time critical and information intensive. For example, people might hurry to prepare presents for the celebration of anniversaries, graduations, and so forth. The value of presents drops rapidly after these events, which means they are time critical. The same story goes for a travel package that people might need to purchase before the vacation starts. However, the presence of various product attributes and many alternatives in these product categories would make people search thoroughly in order to make the right choice among all the products. Therefore, we can consider them to be high in information intensity.

Water, Soda, Coffee, Rice, Dried Foods, Detergents, Paper Towels, and Confectionaries were classified into Quadrant III. These are everyday products that, by and large, are well known to people. These products involve neither time-sensitive transactions nor extensive information searches.

Finally, Laptops, Televisions, Refrigerators, Furniture, Washing Machines, and Sound Systems were classified into Quadrant IV. Products in these categories rarely involve time-critical transactions, but assessing the value of the products in these categories would require extensive information searches because of their complex product attributes (e.g., technological functions and design) as well as service attributes (e.g., warranty conditions).

Table 4 presents the results of comparing the baseline projections and the actual transactions for each quadrant. First, we found evidence of significant substitution of the online channel by the mobile channel in Quadrant I. The number of orders in the online channel dropped by 8.8 percent, on average, after the introduction of the mobile channel. Also, the size of the orders decreased by 18.4 percent. As a result, the average daily revenue in the online channel decreased by 7.4 percent. This supports our prediction that the mobile channel can be an effective substitute for the online channel for Quadrant I. In addition, the mobile channel generated a large new demand of its own (approximately 18 percent of the total transactions in the postintroduction period; the largest among the four quadrants), which more than offset the substitution effect, resulting in an 8.3 percent overall revenue increase for the e-market.

Second, we found a strong complementary effect in Quadrant II. The transactions in the online channel experienced a substantial increase (28.2 percent), on average, after the introduction of the mobile channel, while there was no significant change in the order size. Note that the demand generation on the mobile channel was the smallest among the four quadrants (5.7 percent of the total transactions), possibly due to the low fit with the products. This result supports our conjecture that the mobile channel would significantly boost online transactions. The overall revenue of the e-market increased by 38.2 percent after the mobile channel introduction (the largest increase of the four quadrants).

Third, in Quadrant III, our results suggest that the demand in the online channel was boosted (a 22.4 percent increase) by the introduction of the mobile channel, which is consistent with our prediction. However, the average order size decreased by 27.8 percent, which is significantly larger, compared to the other quadrants. As a result, the revenue in the online channel decreased by 9.3 percent. In sum, we find
Table 4. Baseline Projections and Actual Transactions by Quadrant

<table>
<thead>
<tr>
<th>Variable</th>
<th>Channel</th>
<th>Quadrant I Baseline</th>
<th>Quadrant I Actual</th>
<th>Quadrant II Baseline</th>
<th>Quadrant II Actual</th>
<th>Quadrant III Baseline</th>
<th>Quadrant III Actual</th>
<th>Quadrant IV Baseline</th>
<th>Quadrant IV Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Orders</td>
<td>Online</td>
<td>65.6 (1.1)</td>
<td>58.0 (1.3)</td>
<td>14.2 (0.8)</td>
<td>18.2 (0.8)</td>
<td>101.1 (2.1)</td>
<td>123.7 (2.4)</td>
<td>40.5 (0.7)</td>
<td>47.6 (0.9)</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>— (0.6)</td>
<td>12.5 (0.6)</td>
<td>— (0.1)</td>
<td>1.1 (0.1)</td>
<td>— (0.9)</td>
<td>15.3 (0.9)</td>
<td>— (0.3)</td>
<td>5.1 (0.3)</td>
</tr>
<tr>
<td>Size of Orders</td>
<td>Online</td>
<td>20.6 (0.4)</td>
<td>16.8 (0.3)</td>
<td>35.5 (1.9)</td>
<td>36.9 (2.6)</td>
<td>16.9 (0.2)</td>
<td>12.2 (0.1)</td>
<td>112.8 (0.9)</td>
<td>106.2 (2.3)</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>— (0.9)</td>
<td>15.8 (0.9)</td>
<td>— (4.3)</td>
<td>20.9 (4.3)</td>
<td>— (0.9)</td>
<td>11.4 (0.9)</td>
<td>— (3.5)</td>
<td>59.42 (3.5)</td>
</tr>
<tr>
<td>Revenue</td>
<td>Online</td>
<td>1,177.6 (27.7)</td>
<td>1,090.6 (30.4)</td>
<td>462.3 (24.7)</td>
<td>616.7 (40.2)</td>
<td>1,641.7 (30.0)</td>
<td>1,489.0 (29.5)</td>
<td>4,309.2 (83.5)</td>
<td>5,061.1 (141.3)</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>— (11.0)</td>
<td>184.5 (8.9)</td>
<td>— (8.9)</td>
<td>22.4 (10.3)</td>
<td>— (10.3)</td>
<td>152.9 (29.8)</td>
<td>— (29.8)</td>
<td>313.4 (29.8)</td>
</tr>
<tr>
<td>Total</td>
<td>Online</td>
<td>1,177.6 (27.7)</td>
<td>1,275.1 (33.8)</td>
<td>462.3 (24.7)</td>
<td>639.1 (40.5)</td>
<td>1,641.7 (30.0)</td>
<td>1,641.9 (33.2)</td>
<td>4,309.2 (83.5)</td>
<td>5,374.5 (149.2)</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>— (11.0)</td>
<td>184.5 (8.9)</td>
<td>— (8.9)</td>
<td>22.4 (10.3)</td>
<td>— (10.3)</td>
<td>152.9 (29.8)</td>
<td>— (29.8)</td>
<td>313.4 (29.8)</td>
</tr>
</tbody>
</table>

Notes: Size is in U.S. dollars. Standard errors are in parentheses. As a robustness check, we repeated the analysis after removing the product categories that had the lowest level of agreement among the four authors who rated them. These included Diapers in Quadrant I, Event/Party Products in Quadrant II, Detergents and Dried Food in Quadrant III, and Sound Systems in Quadrant IV. We obtained qualitatively similar results. The Appendix provides additional related information. * p < 0.05; ** p < 0.01; *** p < 0.001.
a net complementary effect in the number of orders, but the revenue effect on the online channel turned out to be negative because of the large drop in the order size. Because the mobile channel generated a substantial demand of its own (11 percent of the total transactions), however, the net impact on the overall revenue of the e-market was not significant.

Finally, in Quadrant IV, we found a moderate complementary effect of the mobile channel. The mobile channel introduction triggered an increase in online transactions by 17.5 percent, while decreasing the average order size by 5.9 percent. The net impact on revenue for the online channel was an increase of 17.4 percent. The mobile channel generated new demand (about 9.7 percent of the total transactions in the postintroduction period), and the overall impact of the mobile channel introduction on the e-market revenue was a 24.7 percent increase. While we expected minimal effects of the mobile channel introduction in this quadrant, the actual effects turned out to be quite significant, although the impact on the Number of Orders and Size of Orders is smaller than in Quadrant III, whose information intensity is lower than that of Quadrant IV.

Discussion

Summary and Discussion of Findings

Overall, we found that the mobile channel does not substitute for, but rather complements, the traditional online channel. In particular, the introduction of the mobile channel significantly increased the number of orders on the online channel while reducing the size of orders somewhat, leading to an overall increase of 5.6 percent in the online channel. By accounting for the additional demand generated by the mobile channel, the introduction of the mobile channel increased the overall revenue from channel adopters by 18.4 percent.

Our key findings concern the differential effect of the mobile channel introduction, depending on two product characteristics: time criticality and information intensity. First, for products with high time criticality and low information intensity, the mobile channel substitutes for the online channel because the former outperforms the latter. However, 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 for products whose characteristics fit the mobile channel’s capabilities better than those of the online channel.

Second, in contrast, regarding products with high time criticality and high information intensity, we found a strong synergy between the online channel and the mobile channel. This is because the mobile channel complements the online channel in time-critical searches and triggers additional transactions on the online channel, substantially boosting the revenue on the latter channel, as well as the total revenue. Transactions generated on the mobile channel are very limited though, since the time-critical search
triggered by the presence of the ubiquitous mobile channel is most likely to be followed by an extensive search and purchase on the online channel.

Third, for products with low time-criticality and low information-intensity, the mobile channel increases online channel transactions while generating substantial transactions of its own. This result is consistent with our prediction based on the availability effect of the mobile channel introduction. Given that both channels fit this product category well, consumers can benefit from the availability of an additional attractive channel (i.e., the mobile channel), which leads to a significant new demand generation. Because the products are not time critical, the generated demand may be realized on either channel, boosting the transactions on both channels. We did not find a significant change in the total revenue though because the increase in the number of transactions is offset by the decrease in the order size. A possible explanation is that the availability of the mobile channel may have resulted in order dispersion between the two channels (i.e., consumers splitting their purchases across the two channels that might otherwise have been made via the online channel without the mobile channel).

Finally, we found that the mobile channel introduction has a moderate complementary effect on the online channel for products with low time criticality and high information intensity. Whereas the online channel fits this product category well, the mobile channel is relatively unattractive because it is not suitable for processing intensive information. Consistent with this explanation, we found that the mobile channel has a smaller impact on the number of online orders compared to Quadrant II, which is more time critical, and on the size of the orders compared to Quadrant III, which is less information intensive. It is somewhat surprising that the transactions on the online channel increased by almost 18 percent after the mobile channel introduction. This may be because of the availability of a ubiquitous channel: although the mobile channel is not suitable for extensive searches, its availability, to some extent, can induce consumers to conduct initial searches for basic information on their mobile devices, which can trigger extensive searches and purchases on their PCs.

Contributions and Implications

Our study makes several important contributions. First, we examined the performance effects of the mobile channel on the online channel. Most of the previous studies have analyzed the impact of channel introduction in the context of offline, online, and catalog channels. Our study expands the scope of the inquiry into the emerging mobile channel and advances our knowledge of multichannel interactions and effects. Although there have been a few studies on the online mobile multichannel system [27, 28], they have focused on the impact of the mobile channel as a service channel. With the striking shift in the information search and transaction environment caused by mobile innovation, we contribute to this nascent literature by investigating the cross-channel and performance effects of the mobile channel as a commerce channel for search and transaction on consumer products.

Second, building on the notion of channel capability by Avery et al. [4] and extending their work, this study contributes to the literature on multichannel strategies
by proposing a theoretical framework that links channel capabilities with product characteristics to assess the differential effects of a new channel introduction across various product categories. While the previous research on cross-channel effects has examined the aggregate, overall impact of a new channel introduction, this study provides a deeper understanding of the interactions between channels by examining the product category-level impact of a mobile channel introduction. The empirical evidence we derived from our data set supports our theoretical framework and predictions. Considering that the product-channel fit within a given channel may not be uniform for all products, this study offers new insights into the interplay between product characteristics and channel capabilities, and can provide a theoretical basis for subsequent multichannel research.

Our final contribution lies in the methodological approach we employed. As a counterfactual analysis approach, a multivariate baseline analysis with vector autoregression does not rely on data from the unaffected group (the nonadopter group in this study), but on data from the affected group itself (the adopter group in this study) to constitute a control group for a comparison of effects. As such, it allows a counterfactual analysis of the effect of a focal factor (the mobile channel introduction in this study) on multiple dependent variables when the available data are limited to those exposed to the focal factor. We believe that this counterfactual method can be useful in evaluating the impact of IT-related events on various performance measures.

This study also provides important managerial implications concerning multichannel strategies. Channel decisions should be understood as strategic choices for achieving market coverage and competitive advantage [2]. Once the choices have been made, managers need to decide what the function of each channel should be and how resources should be allocated across channels [42]. We offer a number of implications for e-commerce firms regarding how to craft effective multichannel strategies for online and mobile channels in terms of the decision to introduce a mobile channel and the mobile channel’s role and functionality.

First, this study presents a general, but important, principle about mobile channel introduction. Our results suggest that e-commerce firms should be cautious before rushing to add a mobile channel: it may not be a one-size-fits-all channel in all performance dimensions, especially when the associated costs are accounted for. Managers need to understand that introducing a mobile channel does not guarantee a prompt, substantial gain in performance, contrary to the highly promising assertion that has been made often; instead, a prudent and critical analysis is called for regarding the potential effects on and strategic options for their businesses. The framework we proposed in this study, which links channel capabilities and product characteristics, can guide the analysis process. Online retailers need to evaluate their products in terms of time criticality and information intensity, using the criteria we have suggested. E-markets or shopping malls should evaluate each of the product categories they are carrying and aggregate the evaluations to assess the overall business impact.

Our second implication concerns the mobile channel’s role and functionality. It will be crucial for firms to specify the role of the mobile channel in their multichannel systems, considering the product-channel fit. For example, online retailers of time-critical
and information-intensive products can aim to strengthen their online performance by launching a mobile channel. Due to the ubiquitous access that is offered, the new channel can make up for the weakness of the existing online channel, thus facilitating timely searches for product information on the former and converting the searches into new transactions on the latter. The retailers operating in this quadrant should be the most active in deploying a mobile channel. Once the objectives are set, several alignments should follow. The mobile channel can be positioned mainly as an informational channel that prompts initial searches for products that can be subsequently purchased on the online channel. Thus, considering the limited usability of mobile devices, it might be better to provide only the essential product information on the mobile channel, which may trigger more thorough searches on the online channel that can display more complete information on the products. Greater efforts need to be made to provide a seamless connection between mobile and online searches, such as showing recent mobile search items on the online screen.

Retailers of less time-critical and less information-intensive products can implement the mobile channel as a sales channel, although they are advised to establish an objective derived from a long-term perspective on the mobile channel. The performance effect of a mobile channel introduction may appear unsatisfactory for those products because there may be a substitution effect for the online channel, as our framework suggests, and there may be no significant increase in the overall revenue, as our results show. However, the increase in transaction frequency that we found for these product categories can contribute to long-term performance by inducing future purchases [15] and by reinforcing the habit of channel usage [35]. This is supported by Liu and Shih [36], who suggested that the effect of frequency overrides that of monetary value.

Conclusion

We developed a theoretical framework that can guide a firm’s decisions to introduce a mobile channel and inform their multichannel strategies. In particular, our framework focuses on linking channel capabilities (access and search) and product characteristics (time criticality and information intensity) relevant to mobile and online channels. By applying the framework to a large data set from a Korean e-market, we showed that our framework can predict and explain the differential effect of mobile channel introduction across different product categories. The fact that our empirical findings are consistent with the predictions we made based on the framework demonstrates that our product-channel fit framework can provide a useful perspective for assessing the impact of adding a mobile channel. With the increasing importance of mobile devices and search, and transaction media use driven by the increasing bandwidth and speed of mobile Internet, many e-commerce firms are jumping on the mobile bandwagon, adding mobile channels to their existing online channels. Our study will provide firms with guidance on the interactions between the channels and the associated multichannel strategies.

We conclude by articulating a few limitations. First, in our theoretical framework, we considered ubiquity and usability as two characteristics that distinguish online
and mobile channels in terms of channel capabilities. While the two are most salient in the context of our study, there are other characteristics that can be derived from the features of technologies underlying the two channels. For example, localization leveraged by location-specific information, in the form of location-based services or location-based advertising, is one such characteristic. It has been suggested as a major advantage of mobile commerce over traditional e-commerce [29, 47]. Although localization is mainly relevant to the context of transactions in an offline-mobile multichannel system, e-commerce firms may also utilize localization to provide context-related product information and promotions. Therefore, localization may distinguish the mobile channel from the online channel, and incorporating it will enrich our framework. In addition, our argument about ubiquity in the framework is focused on its temporal aspect of anytime access, linking it to the product characteristic of time-criticality, while ignoring the spatial aspect of anywhere access from ubiquity. The spatial aspect may be partly correlated with the temporal aspect in some instances because anywhere access enables anytime access. We acknowledge that the spatial aspect of ubiquity can be a salient feature on its own, especially in offline transactions with a mobile information channel.

Second, the empirical analysis was based on the classification of products into four quadrants. Although we carefully classified the products based on multiple criteria and showed some robustness in our analysis results, the classification was essentially subjective rather than objective, which is a challenge associated with any classification process involving human raters (e.g., [23, 25]). Therefore, the criteria for rating each product characteristic need to be refined and validated by future studies.

Third, because of the nascent stage of the mobile channel introduction, the data set in this study includes mostly early adopters of mobile commerce. The logic behind our predictions about the impact of the mobile channel does not depend on the characteristic of the channel adopters; rather, it is based on the characteristics of the channels and products. Therefore, we believe that the results of the current study would not be affected by the adoption stage of the mobile channel users. Nevertheless, an investigation across consumers in various adoption stages could provide additional insights into the dynamics of the mobile channel’s impact by adding a time dimension to our framework.

Finally, in this study, competition was not explicitly incorporated. Although the exogenous variables used in the VARX model, such as market size, market share, and Herfindahl indices are related to competition, and new demand generation by the mobile channel implies that the demand partially comes from competitors, we could not incorporate competition because our data come from a single e-market. Collecting data from multiple competing e-markets and examining the impact of a mobile channel introduction on competitors’ transactions, as well as its own transactions, will be an interesting avenue for future research.

Acknowledgments: The authors thank the guest editors, Eric Clemons, Kim Huat Goh, Rob Kauffman, and Thomas Weber, and three anonymous reviewers for their helpful comments and suggestions. They also thank the Social Science and Humanities Research Councils of Canada, the Desautels Faculty of Management at McGill University, and Hansung University for generous financial support.
NOTES

1. As of June 2012, Korea ranked first in wireless broadband Internet subscription [43]. It has been a leader in mobile commerce adoption with the share of mobile commerce accounting for 17 percent of the total e-commerce sales [41].

2. The consumer purchase decision process is commonly conceptualized to have five stages, including need recognition, information search, alternative evaluation, purchase, and outcome [14]. Access and search capabilities are mainly related to information search, alternative evaluation, and purchase stages.

3. We include cancellations, returns, and exchanges in our analyses because they influence revenue, one of our performance variables. In the Results section, however, we do not report them for expositional brevity.

4. We tested the stationarity of our variables using the augmented Dickey–Fuller test. The test results suggest that we can reject the null hypothesis of a unit root at the 95 percent confidence level.

5. We validated our model by applying it to the nonadopter group. We tested for each of the model variables to determine whether there is a statistical difference between the baseline projections from the VARX model and the actual transactions. No significant difference was found, which supports the validity of our model.

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41. Nakajima, S. World Internet markets. DigiWorld by IDATE Blog, November 22, 2012 (available at blog.idate.fr/world-internet-markets/).
Appendix: Robustness Check for the Main Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Quadrant I without diapers</th>
<th>Quadrant II without event/party products</th>
<th>Quadrant III without detergents and dried food</th>
<th>Quadrant IV without sound systems</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Actual</td>
<td>Baseline</td>
<td>Actual</td>
</tr>
<tr>
<td><strong>Number of Orders</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online</td>
<td>61.6</td>
<td>54.5</td>
<td>12.2</td>
<td>16.0</td>
</tr>
<tr>
<td></td>
<td>(1.22)</td>
<td>(1.10)</td>
<td>(0.6)</td>
<td>(0.6)</td>
</tr>
<tr>
<td></td>
<td>↓ 11.5%***</td>
<td>↑ 31.1%***</td>
<td>↑ 22.4%***</td>
<td>↑ 26.0%***</td>
</tr>
<tr>
<td>Mobile</td>
<td>—</td>
<td>11.9</td>
<td>—</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>(0.6)</td>
<td></td>
<td>(0.1)</td>
<td></td>
</tr>
<tr>
<td><strong>Size of Orders</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online</td>
<td>20.4</td>
<td>16.6</td>
<td>38.2</td>
<td>39.6</td>
</tr>
<tr>
<td></td>
<td>(0.3)</td>
<td>(0.5)</td>
<td>(1.2)</td>
<td>(3.1)</td>
</tr>
<tr>
<td></td>
<td>↓ 18.6%***</td>
<td></td>
<td>↑ 30.5%***</td>
<td></td>
</tr>
<tr>
<td>Mobile</td>
<td>—</td>
<td>15.6</td>
<td>—</td>
<td>22.5</td>
</tr>
<tr>
<td></td>
<td>(0.9)</td>
<td></td>
<td>(4.4)</td>
<td></td>
</tr>
<tr>
<td><strong>Revenue</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online</td>
<td>1,107.3</td>
<td>1,008.1</td>
<td>444.6</td>
<td>589.3</td>
</tr>
<tr>
<td></td>
<td>(25.3)</td>
<td>(29.8)</td>
<td>(26.5)</td>
<td>(39.4)</td>
</tr>
<tr>
<td></td>
<td>↓ 9.0%***</td>
<td>↑ 32.5%***</td>
<td>↑ 12.6%***</td>
<td>↑ 12.0%***</td>
</tr>
<tr>
<td>Mobile</td>
<td>—</td>
<td>182.0</td>
<td>—</td>
<td>22.1</td>
</tr>
<tr>
<td></td>
<td>(10.3)</td>
<td></td>
<td>(8.9)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,107.3</td>
<td>1,190.1</td>
<td>444.6</td>
<td>611.4</td>
</tr>
<tr>
<td></td>
<td>(25.3)</td>
<td>(32.7)</td>
<td>(26.5)</td>
<td>(39.8)</td>
</tr>
<tr>
<td></td>
<td>↑ 7.5%**</td>
<td>↑ 37.5%***</td>
<td>Not significant</td>
<td>↑ 18.9%***</td>
</tr>
</tbody>
</table>

Notes: Size is in U.S. dollars. Standard errors are in parentheses. * p < 0.05; ** p < 0.01; *** p < 0.001.