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The Dark Side of Mobile Channel Expansion Strategies

Ju-Yeon Lee, Mengzhou Zhuang, Irina V. Kozlenkova, and Eric (Er) Fang

Report Summary

Responding to the exponential growth of smartphone usage, many firms have added mobile channels to their existing online channels. In this study, Ju-Yeon Lee, Mengzhou Zhuang, Irina Kozlenkova, and Eric Fang investigate the potential adverse consequences of a mobile channel expansion strategy.

Study 1, using data from a leading online shopping platform, shows that the mobile shopping ratio (proportion of the purchase occasions conducted on mobile devices relative to total online purchase occasions) exhibits an inverted U-shaped relationship with sales performance. This is due to the combined effects of increased transaction frequency and decreased transaction spending (i.e., mobile customers shop more often but spend less).

The researchers find that heavy mobile shoppers yield higher sales by buying more frequently overall, but they spend less on each purchase, such that customers with moderate mobile shopping ratio levels (i.e., multichannel shoppers) are more beneficial than heavy or light mobile shoppers. A post hoc analysis affirms that customers are most profitable when they choose mobile devices about once out of every three online shopping occasions.

Transaction-level analysis also shows that orders through mobile devices contain 20% cheaper and 7% fewer products than orders through other online devices. These negative effects are mitigated when customers purchase low-risk products or buy from high-quality sellers.

Study 2, analyzing secondary data from about 200 publicly traded U.S. firms, shows that the effect of a mobile expansion strategy on stock returns is positive when the mobile traffic ratio (proportion of visits customers make on mobile devices relative to total online visits) is low, but becomes increasingly negative at higher levels.

The negative effect on stock returns at high mobile traffic ratio levels is alleviated in firms with high operating efficiency or low website cognitive load. Firms can maximize their financial performance when about half of their online visitors enter through smartphones, but in a firm with a low website cognitive load, performance does not diminish until the mobile traffic ratio reaches 64%.

Overall, these findings suggest that managers should avoid overextending into mobile channels and instead seek to maintain a balance across different online channels. Further, when undertaking a mobile channel expansion strategy, companies should (1) prominently display indications of seller quality, such as consumer reviews, to facilitate decision-making, especially for risky products, (2) improve operating efficiency, and (3) develop websites that do not demand much cognitive effort from consumers to navigate via mobile channels.

Ju-Yeon Lee is Assistant Professor of Marketing, College of Business and Economics, Lehigh University. Mengzhou Zhuang is a doctoral student in marketing, College of Business, University of Illinois at Urbana-Champaign. Irina V. Kozlenkova is Assistant Professor of Marketing, Eli Broad College of Business, Michigan State University. Eric (Er) Fang is Associate Professor of Marketing and James Tower Faculty Fellow, University of Illinois at Urbana-Champaign, and Distinguished Visiting Professor of Marketing, Nanjing University, China.

Mobile channels have become a major boardroom topic, especially as the penetration of smartphones in the United States surpassed 70% in 2014 (comScore 2014). Almost 60% of firms place “mobile at the top of their marketing priority lists” (National Retail Federation 2015a), noting that more than one-third of online U.S. customers shop on mobile devices, and mobile sales are projected to exceed $280 billion worldwide (*Forbes* 2015b). Responding to demand, firms have added mobile channels, and in parallel, researchers have generally recommended that firms should invest in mobile channels, because mobile shopping can yield higher order frequency (Wang, Malthouse, and Krishnamurthi 2015) and increased customer loyalty (Shankar et al. 2010). Yet despite this prevailing optimism, expanding to a mobile channel may have some unforeseen and negative ramifications; for example, industry reports show that as more customers shift to mobile shopping, “average order value would come down” (*Washington Post* 2015b), and they limit their purchases to small-ticket items (*Fortune* 2014). With these concerns, it is surprising that extant marketing research has overlooked the dark side of mobile channels.

This article investigates the adverse consequences of a *mobile channel expansion strategy*, as reflected by the degree to which customers have adopted a firm’s mobile channel. Our findings across multiple levels—transaction, customer, and firm—provide strong evidence that a firm’s mobile channel expansion strategy undermines business performance once it passes a certain threshold. To capture the mobile channel expansion strategy concept, we assess the share of online sessions conducted through mobile devices with two parallel measures. First, we consider consumers’ *mobile shopping ratio*, or the proportion of the purchase occasions they conduct on mobile devices, relative to total online purchase occasions. Second, we measure *mobile traffic ratio*, or the proportion of visits customers make on mobile devices relative to their total online visits. These parallel, complementary measures offer two major benefits. By using a mobile shopping ratio, we gain in-depth insights into customer behavior on mobile devices in an online shopping context; the mobile traffic ratio enables us to generalize the findings to firms with business models that rely on selling ad placements (e.g., pay-per-click, pay-per-view) instead of operating shopping interfaces. The mobile shopping ratio also allows us to evaluate the effect of consumers’ mobile purchasing patterns on sales numbers (internal valuation of the mobile channel), and the mobile traffic ratio reveals the effect of consumers’ mobile usage patterns on financial values assessed by investors (external valuation of the mobile channel). Thus, our dual approach to the effectiveness of mobile channel expansion can answer some of the priority questions for mobile channels set by the Marketing Science Institute (2014).

By mapping these parallel measures of mobile channel expansion strategy in two studies, we empirically examine the performance implications at transaction, customer, and firm levels. In Study 1, using customer-level data from 14,208 valid customers who made purchases on a leading online shopping platform over two years (June 2012–June 2014), we find that the mobile shopping ratio exhibits an inverted U-shaped relationship with sales performance, due to the combined effects of increased transaction frequency and decreased transaction spending (i.e., mobile customers shop more often but spend less). To detail the negative effects of mobile shopping, we then shift to the transaction level and find that the decline in transaction spending results because customers tend to buy fewer, lower priced products in each mobile transaction than in other online transactions. To generalize our findings from Study 1, we analyze firm-level multisource secondary data of publicly traded U.S. firms over seven months (June–December 2014) and find that the effect of a mobile expansion strategy on stock returns is positive at low levels of the mobile traffic ratio but becomes increasingly negative beyond a critical point. Thus, our two multilevel studies provide clear evidence of the dark side of mobile channels.

In turn, this research makes four key contributions. First, we offer insights into the painful tensions associated with a mobile channel expansion strategy. In Study 1, we identify two underlying mechanisms through which customers' mobile shopping ratio affects sales performance: transaction frequency and transaction spending (i.e., sales = frequency × spending). Each factor comes in conflict, such that heavy mobile shoppers yield higher sales by buying more frequently (increased frequency) overall, but they spend less (decreased spending) on each purchase. These trade-offs produce the inverted U-shaped net effect of mobile shopping on customer sales, such that customers with moderate mobile shopping ratio levels (i.e., multichannel shoppers) are more beneficial than heavy or light mobile shoppers. Our post hoc analysis affirms that customers are most profitable when they choose mobile devices about once out of every three online shopping occasions (optimal mobile shopping ratio = 38%). In contrast with Wang, Malthouse, and Krishnamurthi (2015), who proposed that mobile shopping increases both order size and rate, we find clear support for the hypothesis that mobile shopping has adverse effects. Mobile channels seem to eclipse other online channels, but our findings are in line with the view that "many [firms] are making big investments to build easy-to-use mobile sites…, and yet they cannot neglect the traditional Web presence that still pulls down the lion's share of shoppers' money" (*Washington Post* 2015a).

Second, to understand how the mobile shopping ratio reduces transaction spending, we move down to the transaction level and specify the decisions that customers make. Transaction spending reflects product price and product quantity (transaction spending = product price × product quantity), so we decompose it into these two underlying components. Our findings suggest that transactions through mobile devices consist of fewer and less expensive products than other online transactions (personal computers), due to consumers' insecurity and the limited display size associated with mobile devices. Our model-free evidence indicates that orders through mobile devices contain 20% cheaper and 7% fewer products than orders through other online devices. We thus empirically and theoretically identify the mediating mechanisms that cause mobile channel expansion strategies to damage business outcomes.

Third, we examine *seller quality* and *product risk* as factors that might moderate the effects of the mobile shopping ratio on sales performance. Our customer-level analysis shows that for customers who tend to buy from sellers with higher ratings or purchase lower risk products (e.g., office products versus fine jewelry), the positive effect of the mobile shopping ratio on transaction frequency is greater, whereas the negative effect of the mobile shopping ratio on transaction spending gets suppressed. Similarly, a transaction-level analysis reveals that when orders consist of products sold by better quality sellers or that invoke minimal risk, the negative effect of mobile transactions on product price and product quantity is alleviated. In summary, mobile customers are more profitable to the firm when they purchase from highly rated sellers and shop for products with less perceived risk, such as books and office supplies.

Fourth, we generalize the dark side of a mobile channel expansion strategy by showing that the mobile traffic ratio generates more stock returns, yet after a point, it becomes counterproductive. The negative effect of mobile traffic on stock returns at high levels of the mobile traffic ratio may be alleviated in firms with high operating efficiency, low website cognitive load, or an absence of online stores. Firms can maximize their financial performance when about half of their online visitors enter through smartphones (optimal mobile traffic ratio = 51%), but in a firm with a low website cognitive load, performance does not diminish until the mobile traffic ratio reaches 64%. Managers thus should avoid overextending into mobile channels and instead seek to maintain a balance across different online channels.

Understanding Mobile Channels

Research increasingly emphasizes the importance of mobile e-commerce (Parasuraman and Zinkhan 2002; Payne and Frow 2005) and suggests that firms should expand to mobile channels to serve customers, because offering a multichannel platform enhances customer loyalty and demand (Xu et al. 2014). Marketing scholars identify four characteristics of a mobile channel that distinguish it from other online or traditional channels, as we summarize in Table 1. First, mobile channels are characterized by ubiquity and universality (Watson et al. 2002), because they are "completely spatially and temporally flexible" (Balasubramanian, Peterson, and Jarvenpaa 2002, p. 351). Second, the use of a mobile channel augments customers' perceived psychological ownership of products, because it is not shared by other individuals (Brasel and Gips 2014). Third, mobile channels provide limited display sizes and low communication speed (Shugan 2004). Fourth, customers using mobile channels perceive higher risks of information and monetary losses (Kleijnen, de Ruyter, and Wetzels 2007). Although ubiquity and increased psychological ownership may give customers more opportunity to shop and increase their purchase frequency, the limited display size and higher risk of losses may deter them from making big purchases through their phones.

In an extensive literature review, we find two major limitations in existing research. In particular, no studies offer a holistic view of the trade-offs associated with mobile channels. Most research on mobile channels focuses on the antecedents of mobile shopping (e.g., Ko, Kim, and Lee 2009; Koenigstorfer and Groeppel-Klein 2012; Lu and Su 2009; Sultan, Rohm, and Gao 2009) rather than its performance implications. To our knowledge, only one empirical study examines the effect of mobile shopping on business outcomes (Wang, Malthouse, and Krishnamurthi 2015), and it does not address any possible detrimental effects stemming from the characteristics of mobile channels (e.g., small screen, security threats). Furthermore, many studies examine mobile app usage (Ghose, Goldfarb, and Han 2013) or mobile promotions (Bart, Stephen, and Sarvary 2014; Fong, Fang, and Luo 2015), but they do not reveal any performance implications of a mobile channel expansion strategy.

To bridge these gaps, we investigate how and when a mobile channel expansion strategy affects performance in two studies. In Study 1 we capture the essence of a mobile channel expansion strategy by using the *mobile shopping ratio* (proportion of purchase occasions that the customer makes through mobile devices, relative to total online purchase occasions) and evaluate its effect on sales performance. In Study 2, we use the *mobile traffic ratio* (proportion of visits made through mobile devices relative to total online visits) to assess its effect on investors' financial performance expectations. Thus, we offer insights into both internal (customer sales) and external (stock market returns) valuations of customers' adoption of mobile channels.

(Tables and figures follow References.)

Study 1: Effect of Customer Mobile Shopping on Sales Performance

In Study 1, we use the mobile shopping ratio to reflect the degree to which a customer uses a mobile channel for shopping, as a proportion of his or her total online purchase occasions. We develop the conceptual framework in Figure 1 to explicate the effect of mobile shopping on customer sales, such that we decompose sales into two main components: transaction frequency and transaction spending. The customer mobile shopping ratio should have opposing effects on these two components.

Decomposing the effects of customer mobile shopping on customer sales

Positive mechanism: Mobile shopping increases transaction frequency. Customers with high mobile shopping ratios should exhibit increased transaction frequencies on all their online devices (including personal computers), for two reasons. First, the ubiquity and universality of mobile devices allow customers to shop anywhere and anytime. Because "mobile technologies can relax both the independent and mutual constraints of space and time" (Balasubramanian, Peterson, and Jarvenpaa 2002, p. 353), the use of mobile devices drives online traffic and helps customers make purchases almost immediately when they have pressing needs, so they place orders more frequently. Second, even if customers do not make a purchase transaction through their mobile device, the instant and easy access they offer improves customers' ability to conduct prepurchase research throughout the purchase journey, such that "A whopping 46% of shoppers reported they exclusively use their mobile device to conduct pre-purchase research" (McGrane 2013). In turn, the frequency of purchases on non-mobile devices such as personal computers should increase too. Because 45% of all mobile searches are goal oriented and conducted to help make a decision (The Nielsen Company 2013), customers who check product and shopping information on mobile devices are more likely to end up purchasing a product through some channel than are those who use mobile devices less frequently. Therefore, we argue that customers with a higher mobile shopping ratio exhibit higher transaction frequency.

Negative mechanism: Mobile shopping decreases transaction spending. In contrast with the positive effect of the customer mobile shopping ratio on transaction frequency, we predict that it decreases transaction spending, for two reasons. First, security and safety concerns with the mobile channel reduce average purchase sizes. Online shopping generally suffers from identity theft and privacy issues; these concerns are more severe for mobile interfaces, because customers perceive few security measures to protect their information, which increases their transaction costs and requires more cognitive effort. For example, 30% of customers worry about providing their credit card information over a mobile connection, and mobile visitors are four times less likely to buy than are desktop visitors (National Retail Federation 2015b). Software and technology on smartphones feels less secure and protective, so shoppers using mobile devices tend to limit their purchases to small-ticket items and "wait until they get to a tablet or computer to buy the expensive stuff" (*Fortune* 2014).

Second, the smaller screen and limited bandwidth of mobile devices prevent customers from getting a clear image or full description of a product; at least, they make it less convenient than doing so on a computer. That is, "screen sizes are smaller on mobile devices compared to PCs, thereby rendering higher search costs for mobile devices" (Ghose and Han 2011, p. 1671). Mobile shopping also reduces cross-selling opportunities, because customers click mostly on the top ranked products through their mobile devices, rather than exploring more product options on their personal computers, and then may end up buying fewer products in the single transaction (Ghose, Goldfarb, and Han 2013). When customers shop on mobile devices, they also tend to buy habitual products that do not require much consideration (Wang, Malthouse, and Krishnamurthi 2015). These products likely involve inexpensive, routine purchases that do not present much risk to customers. Thus, we argue that customers with a higher mobile shopping ratio exhibit a lower level of transaction spending.

Combined effect of transaction frequency and transaction spending: Customer sales. At the customer level, sales equal the product of the customer's transaction frequency and transaction spending (i.e., sales = frequency × spending). Combining our arguments that indicate that the customer mobile shopping ratio increases transaction frequency but decreases transaction spending, we hypothesize an inverted U-shaped relationship between the customer mobile shopping ratio and customer sales, reflecting the process by which "one may also construct an inverted U-curve by interacting two latent linear functions, one positive and one negative in the independent variable" (Haans, Pieters, and He 2016, p. 4). The two opposing mechanisms result in an inverted U-shaped relationship, so customer sales likely peak at intermediate levels of the mobile shopping ratio. Customers who balance purchases across mobile and other channels thus should be more valuable than those who use the mobile channel more.

Extant studies also suggest that multichannel shoppers exhibit lower churn rates, greater loyalty and spending (Neslin et al. 2006), higher revenue, higher share of wallet, and a higher likelihood of remaining active than do single-channel customers (Kumar and Venkatesan 2005). A recent industry report on mobile channels noted that, compared with single-channel customers, multichannel customers were worth 3 to 8 times more for retailers such as Macy's and Target (Think with Google 2015). In summary, at a customer level, customers' cross-device behavior should increase overall customer sales in such a way that the mobile shopping ratio affects performance:

> **H_1:** The customer mobile shopping ratio (a) positively affects transaction frequency and (b) negatively affects transaction spending, such that (c) at lower levels, the ratio positively affects customer sales but after a critical point, the ratio negatively affects customer sales (i.e., inverted U-shaped relationship).

Moderating effect of mobile shopping on customer sales. Seller quality and product risk are factors that might offer guidance into how firms can overcome some negative ramifications that prevent mobile shoppers from generating sales. These two factors determine the degree of uncertainty to which customers are exposed during online shopping, so they enable us to examine the role of online uncertainty and its salience in a mobile shopping interface (Think with Google 2015).

Seller quality refers to the perceived superiority of the seller over peer sellers (Sriram et al. 2015). We draw on signaling theory, according to which signals indicating unobservable quality help resolve problems caused by the information asymmetry that inevitably occurs between buyers and sellers (Kirmani and Rao 2000). Seller quality should enhance the positive effect of the customer mobile shopping ratio on transaction frequency and suppress the negative effect on transaction spending for two reasons. First, high seller quality serves as a signal of reduced risk and uncertainty. Online shopping is generally regarded as risky, but customers generally face more risk on a mobile interface than on other digital channels, due to its higher search costs and security concerns. Signaling theory suggests that on the mobile interface, for which search costs and perceived risk are high, customers likely rely on specific cues to decide whether and which products to purchase. One such signal that customers can easily see and interpret is seller quality, as indicated by the ratings of past customers. Thus, high seller quality can alleviate customers' perceived risks associated with mobile devices and increase confidence that the transaction will result in a good purchase.

Second, seller quality allows customers to lessen the cognitive burden associated with evaluating different products. Due to the input restrictions and limited display capacity, mobile shoppers constantly must scroll (up/down and left/right) and remember the content of web pages they viewed previously, which "increases the cognitive load and the potential for error" (Ghose, Goldfarb, and Han 2013, p. 615). Seller quality serves as a quick indicator that the seller is reliable, so customers can narrow or end their search, proceed with the transaction, and limit or eliminate their cognitive burden. For these two reasons, we propose:

> **H_2:** Seller quality (a) enhances the positive effect of the customer mobile shopping ratio on transaction frequency and (b) suppresses the negative effect of the customer mobile shopping ratio on transaction spending.

Product risk refers to customers' perceptions of uncertainty and the potential for adverse consequences resulting from purchasing a product (Dowling and Staelin 1994), and it consists of five bases: functional (product not performing as expected), financial (loss of money), physical (causing physical harm to the customer), psychological (damaging the customer's self-image), and social (damaging others' perceptions of the customer) (Kushwaha and Shankar 2013). It is critical to understand the role of product risk, which affects customers' purchase intentions (Dillard and Johnson 2015; Kushwaha and Shankar 2013). We argue that heavy mobile shoppers tend to make purchases less frequently and spend even less when purchasing high risk products, such as fine jewelry and computers (versus books and toys). These products require customers to collect more detailed information before making the final purchase; the mobile interface, which does not offer full descriptions or images of the products, instead tend to limit their ability to conduct extensive searches. As such, it may reduce the positive effects of the customer mobile shopping ratio on transaction frequency and further exacerbate the negative effect of this ratio on transaction spending.

> **H_3:** Product risk (a) suppresses the positive effect of the customer mobile shopping ratio on transaction frequency and (b) enhances the negative effect of the customer mobile shopping ratio on transaction spending.

Decomposing the effect of mobile shopping on transaction spending

***Mobile transactions lower product price and quantity*.** Our customer-level analysis shows the trade-offs associated with mobile channels, but it cannot explain *why* heavy mobile shoppers spend less on each order. We therefore switch to the transaction level, which allows us to slice the data in new ways and gain unique insights into the underlying mechanisms. In particular, we decompose transaction spending into product price and product quantity.

Transactions through mobile devices should generally involve lower-priced products than other online transactions. Due to the inherent constraints of mobile devices, such as the small screen size and limited browsing capabilities, customers who shop on smartphones must find a quick and easy way to rank the individual products that they have discovered, before deciding which one(s) to purchase. Customers often choose to display the results sorted by price, from least to most expensive, such that they see the most inexpensive products first. Searching on a mobile device increases cognitive burdens, so mobile customers might not search for long. Combined with their greater price consciousness on average, they therefore are likely to choose inexpensive products listed close to the top of their search results. Furthermore, m-commerce experts contend that mobile shoppers are more price sensitive than typical online shoppers: These "mobile visitors … are highly aware comparison shoppers" and represent "a group that's using a mobile not just to shop, but to shop around" (Walmsley 2011). As such, mobile orders should consist of cheaper items than do other online orders.

We also suggest that transactions made with mobile devices comprise fewer products than other online transactions. Again, mobile shopping hampers customers' ability to view large and clear images of products, easily read extensive product information, and quickly and effortlessly switch back and forth across multiple website pages. In turn, firms are more likely to lose cross-selling opportunities when customers shop on smartphones. The loading time for images of products on mobile devices also is longer than on personal computers, so customers might check options and add fewer items to their mobile shopping carts. Moreover, customers tend to rely on instantaneous purchase functions on mobile devices (Think with Google 2015), which force them to check out before adding more items to their carts. Thus, in the comparison of mobile and other online settings, we predict that customers purchase most of the products they need online, without such obstacles, and leave fewer purchases for mobile transactions.

H_4: Mobile transactions contain (a) lower-priced products (negative effect of mobile transaction on product price), and (b) fewer products (negative effect of mobile transaction on product quantity) than other online transactions.

Moderating the effect of mobile transactions on product price and quantity. In line with our argument in the customer-level analysis, we expect that seller quality mitigates the negative effects of mobile transactions on product price and product quantity. Two reasons customers tend to shop on other online channels (e.g., personal computers) instead of mobile devices are to avoid product images that are too small and unclear or an inability to view product information easily (UPS 2014, 2015). These limitations contribute to the information asymmetry problem between buyers and sellers. We argue that to some extent, seller quality can compensate for these challenges and suppress the negative effect of mobile transactions on product price and quantity.

Many e-commerce websites make seller quality information available to customers; for example, eBay.com indicates the percentage of positive feedback a seller has received from previous customers. According to signaling theory, firms imply the unobservable quality of their products by using observable cues (Kirmani and Rao 2000), such as seller quality. Such signals can be especially helpful to mobile shoppers, who are unable to evaluate the product they are considering directly, such that they can only read product descriptions and look at product images, which is problematic on the small mobile devices. High seller quality therefore offers a signal of a collective willingness to buy among past costumers and reduces risk perceptions, which might mitigate the negative relationships of a mobile transaction with product price or product quantity. As customers' perceived risk decreases, they may be inclined to purchase products that are slightly more expensive, and do so more frequently on their mobile devices, compared with situations in which low seller quality signals an increased level of risk.

H_5: Seller quality suppresses the negative effects of mobile transactions on (a) product price and (b) product quantity.

Customers purchasing high-risk product categories also look for inexpensive products and purchase fewer of them than buyers of low-risk products, because the perceived risks of mobile transactions and customers' inability to conduct thorough research on a mobile device are compounded by the risks associated with the product category. Buying fewer and cheaper products can offset these risks to some extent, by minimizing possible losses. Furthermore, mobile shoppers "want to be able to search, browse and buy products in 60 seconds or less in as few clicks as possible" (Mobile Marketer 2011, p. 9). Arguably, it would be more difficult for mobile shoppers to assess high-risk products properly in a shorter amount of time, so customers may be more likely to pick according to price when purchasing a high-risk product. Thus,

H_6: Product risk enhances the negative effect of mobile transactions on (a) product price and (b) product quantity.

Data

Our data set for Study 1 comes from a leading online shopping platform that maintains both business-to-consumer (B2C) and consumer-to-consumer (C2C) stores. It was founded in 1999 and has become a global e-commerce leader, with 76 million users from more than 70 countries, including 66 million buyers and 10 million sellers who conduct $4.5 billion worth of online transactions daily. Customers can order products through the platform using their personal computers or mobile devices; the platform itself has no physical, offline stores. The platform provided data on the trading activities of randomly sampled customers over two years (June 2012–June 2014). To avoid a customer size bias, we excluded customers in the top 5% and bottom 5% in terms of sales, which left 14,208 valid customers and 218,330 transactions. These transactions involve 368 sellers and 61,190 products. On average, each customer engaged in 15.37 transactions during the data window. In this sample, approximately one-third (34.98%) of customers used a mobile channel at least once, and they used mobile devices to make 20.12% of all purchases over the two-year period. The firm categorizes products into 16 groups, such as clothing/shoes (22.17%), furniture/household (18.68%), foods/nutrition (15.51%), nursing/infant (12.46%), and jewelry (6.09%). Each transaction can contain multiple products if customers order multiple products at once.

Measures

Customer level: Customer sales, transaction frequency, and transaction spending. We measured customer sales as the customer's total shopping expenditures, equal to the total amount of money a customer spent on the shopping platform through all channels. Transaction frequency is the number of transactions. The values of this discontinuous variable can only be integers greater than 0. Transaction spending is the average expenditure per transaction (i.e., sales over transaction frequency).

Transaction level: Product price and product quantity. Product price is the average unit price of the product in a transaction, and product quantity measures the number of products ordered in the transaction. If a customer buys multiple products in a single transaction, the product price is the average unit price (i.e., product price = transaction spending/product quantity). We log transformed both variables to alleviate the skewness in the data (e.g., extremely large or small values).

Transaction and customer levels: Seller quality and product risk. We measure seller quality at two levels. For the transaction-level analysis, seller quality was the customer's rating of the seller involved in the transaction. The platform's rating system is a common, five-star system, such that higher values indicate more customer satisfaction with a specific seller. For the customer-level analysis, we used the aggregated value of seller quality, calculated as the average customer rating of sellers aggregated to the customer level.

We also measured product risk at two levels. At the transaction level, the product risk measure is a dummy variable, indicating whether the transaction contains risky product categories (1 = transaction contains risky product categories, 0 otherwise) (Kushwaha and Shankar 2013). At the customer level, product risk is the percentage of orders containing risky products (i.e., number of orders containing risky products/number of all orders).

Control variables. To control for consumer heterogeneity, we included demographic variables, such as gender, age, membership duration, and geographic location (i.e., city dummy). We also controlled for purchase behavior variables, such as seller popularity, product popularity, and type of commerce (B2C vs. C2C). In Table 2, we describe the constructs, definitions, measures, and data sources. In Panels A and B of Table 3, we summarize the descriptive statistics for all measures used in Study 1.

Model specification

Customer-level analysis: Effect of mobile shopping on customer sales, transaction frequency, and transaction spending. To test H_1–H_3, we analyze variables aggregated at the customer level (customer sales, transaction frequency, transaction spending), which requires panel structure data. Choosing an appropriate time window is important to panel structure construction, because intervals between transactions are generally long, and customers rarely shop with any certain frequency (i.e., average number of orders per month is 1.89, and more than half of customers purchase once per month). A time window that is too narrow would result in inefficient estimations, especially for transaction frequency after taking the first difference; a time window that is too broad could not capture systematic changes in customer sales. We thus divided the data set into three subsamples, each covering an eight-month period. The average number of orders per period per customer was 5.53. The total number of observations was 39,459, and the average number of observations in each subsample was 13,156.

To account for the bias from time-invariant fixed effects, selection, and other potential noise, we took several steps. First, to control for the influences of time-invariant unobserved customer characteristics, we took the first difference of all variables in the regression equation (e.g., Steenkamp and Fang 2011). Second, to correct for self-selection bias, such that customers with high transaction values are more likely to use mobile channels, we included the self-selection correction term (inverted Mill's ratio) in the regression model. At the transaction level, we ran a logit regression model using mobile transaction as the dependent variable and obtained the inverted Mill's ratio of every transaction. We then took the average of the inverted Mill's ratio for all transactions (j) for each customer (i) to aggregate to the customer level and entered it into the main model estimation. Consider the following logit model equation:

$$\begin{aligned}\mathrm{MobileTransaction}_{ij} = {} & \alpha_{00} + \alpha_{01}\mathrm{Gender}_i + \alpha_{02}\mathrm{Age}_i + \alpha_{03}\mathrm{MemberDuration}_i + \\ & \alpha_{04}\mathrm{TypeofCommerce}_{ij} + \alpha_{05}\mathrm{SellerPopularity}_{ij} + \alpha_{06}\mathrm{ProductPopularity}_{ij} + \\ & \alpha_{07}\mathrm{SellerQuality}_{ij} + \alpha_{08}\mathrm{ProductRisk}_{ij} + \alpha_{09}\mathrm{Time}_{ij} + \varepsilon_{0ij}\ , \qquad (1)\end{aligned}$$

where i refers to the i^{th} customer, and j indicates the customer's j^{th} transaction. Finally, we included a time dummy in the model as a covariate to control for time-invariant effects. The sample size for the first three equations was 39,459; after taking the first difference, the valid sample size became 24,810. Following extant literature in marketing (Ludwig et al. 2013), we propose the following model specifications:

$$\begin{aligned}\Delta\,\mathrm{CustomerSales}_{it} = {} & \alpha_{10} + \alpha_{11}\Delta\mathrm{MobileShoppingRatio}_{it} + \alpha_{12}\Delta\mathrm{MobileShoppingRatio}_{it}{}^{2} + \\ & \alpha_{13}\Delta\mathrm{SellerQuality}_{it} + \alpha_{14}\Delta\mathrm{ProductRisk}_{it} + \alpha_{15}\Delta\mathrm{Controls}_{it} + \alpha_{16}\mathrm{Time} + \\ & \alpha_{17}\mathrm{InverseMill'sRatio}_{it} + \alpha_{18}\Delta\mathrm{TransactionFrequency}_{it} + \alpha_{19}\,\Delta\,\mathrm{TransactionSpend}_{it} + \\ & \varepsilon_{1it}, \qquad (2)\end{aligned}$$

$$\begin{aligned}\Delta\,\mathrm{TransactionFrequency}_{it} = {} & \alpha_{20} + \alpha_{21}\Delta\mathrm{MobileShoppingRatio}_{it} + \alpha_{22}\Delta\mathrm{SellerQuality}_{it} + \\ & \alpha_{23}\Delta\mathrm{ProductRisk}_{it} + \alpha_{24}\Delta(\mathrm{MobileShoppingRatio}_{it} \times \mathrm{SellerQuality}_{it}) + \\ & \alpha_{25}\Delta(\mathrm{MobileShoppingRatio}_{it} \times \mathrm{ProductRisk}_{it}) + \alpha_{26}\Delta\mathrm{Controls}_{it} + \alpha_{27}\mathrm{Time} + \\ & \alpha_{28}\mathrm{InverseMill'sRatio}_{it} + \alpha_{29}\,\Delta\,\mathrm{TransactionSpend}_{it} + \varepsilon_{2it}, \text{ and} \qquad (3)\end{aligned}$$

$$\begin{aligned}\Delta\,\mathrm{TransactionSpend}_{it} = {} & \alpha_{30} + \alpha_{31}\Delta\mathrm{MobileShoppingRatio}_{it} + \alpha_{32}\Delta\mathrm{SellerQuality}_{it} + \\ & \alpha_{33}\Delta\mathrm{ProductRisk}_{it} + \alpha_{34}\Delta(\mathrm{MobileShoppingRatio}_{it} \times \mathrm{SellerQuality}_{it}) + \\ & \alpha_{35}\Delta(\mathrm{MobileShoppingRatio}_{it} \times \mathrm{ProductRisk}_{it}) + \alpha_{36}\Delta\mathrm{Controls}_{it} + \alpha_{37}\mathrm{Time} + \\ & \alpha_{38}\mathrm{InverseMill'sRatio}_{it} + \alpha_{39}\Delta\mathrm{TransactionFrequency}_{it} + \varepsilon_{3it}, \qquad (4)\end{aligned}$$

where i refers to the i^{th} customer, and t equals the time period of subsample (t = 1,2,3). The controls include both time-invariant and time-variant information: gender, age, membership duration, seller popularity, product popularity, type of commerce (B2C vs. C2C), city dummy, time dummy, and inverse Mill's ratio. To correct for the interdependence between transaction frequency and spending, we also include transaction spending (frequency) as a control variable when estimating transaction frequency (spending).

Transaction-level analysis: Effect of mobile transactions on product price and quantity. To empirically test H_4–H_6, we further decompose transaction spending into product price and product quantity. To control for customer heterogeneity, we adopt a weighted least square approach, where the inverse of the customer's transaction frequency provides the weight. This approach helps correct for any overestimation of customers with high purchase frequency. The sample size (i.e., number of valid transactions) is 218,330. We thus propose the following model specification:

$$\begin{aligned}\mathrm{ProductPrice}_{ijt} = {} & \beta_{10} + \beta_{11}\mathrm{MobileTransaction}_{ijt} + \beta_{12}\mathrm{SellerQuality}_{ijt} + \beta_{13}\mathrm{ProductRisk}_{ijt} + \\ & \beta_{14}\mathrm{MobileTransaction}_{ijt} \times \mathrm{SellerQuality}_{ijt} + \beta_{15}\mathrm{MobileTransaction}_{ijt} \times \\ & \mathrm{ProductRisk}_{ijt} + \beta_{16}\mathrm{Controls}_{ijt} + \beta_{17}\mathrm{ProductQuantity}_{ijt} + \varepsilon_{4ijt}\text{, and} \qquad (5)\end{aligned}$$

$$\begin{aligned}\mathrm{ProductQuantity}_{ijt} = {} & \\ & \beta_{20} + \beta_{21}\mathrm{MobileTransaction}_{ijt} + \beta_{22}\mathrm{SellerQuality}_{ijt} + \beta_{23}\mathrm{ProductRisk}_{ijt} + \\ & \beta_{24}\mathrm{MobileTransaction}_{ijt} \times \mathrm{SellerQuality}_{ijt} + \beta_{25}\mathrm{MobileTransaction}_{ijt} \times \\ & \mathrm{ProductRisk}_{ijt} + \beta_{26}\mathrm{Controls}_{ijt} + \beta_{27}\mathrm{ProductPrice}_{ijt} + \varepsilon_{5ijt}\text{,} \qquad (6)\end{aligned}$$

where i refers to the i^{th} customer, and j indicates the customer's j^{th} transaction in time window t (t = 1,2,3). The controls again included both time-invariant and time-variant information: gender, age, membership duration, seller popularity, product popularity, type of commerce (B2C vs. C2C), city dummy, and time dummy. We also used the customer's mobile shopping ratio in the prior stage to capture the customer's general mobile purchase tendency toward price and quantity at the transaction level (Wang, Malthouse, and Krishnamurthi 2015) and the inverse Mill's ratio at the transaction level for the self-selection bias. Finally, to account for interdependence between product price and quantity, we included product price (quantity) as a control variable when estimating product quantity (price).

Results and discussion

Customer-level estimation results. As Models 2 and 4 of Table 4 indicate, increases in the mobile shopping ratio would lead to a significant increase in transaction frequency (b = .033,

$p < .01$) but a significant decrease in transaction spending (b = -.014, $p < .05$), in support of H_{1a} and H_{1b}. Put differently, frequent smartphone shoppers tend to make purchases more often but spend less each time they shop. Combining two opposite linear functions, we find that a customer's mobile shopping ratio has a significant positive first-order effect (b = .051, $p < .01$) and a significant negative second-order effect (b = -.49, $p < .01$) on customer sales (Model 1 of Table 4). The results suggest that the increments of customer sales would be the highest when customers exhibit a moderate mobile shopping ratio, in support of H_{1c}.

As we predicted in H_{2a} and H_{2b}, high seller quality enhances the positive effect of the mobile shopping ratio on transaction frequency (b = .024, $p < .01$) but weakens the negative influence of the mobile shopping ratio on transaction spending (b = .016, $p < .05$). In support of H_{3a} and H_{3b}, high product risk weakens the positive impact of the mobile shopping ratio on transaction frequency (b = -.016, $p < .01$) but enhances its negative influence on transaction spending (b = -.015, $p < .05$).

Transaction-level estimation results. As Models 1 and 3 of Table 5 indicate, relative to other online channel transactions, mobile transactions lower both product price (b = -.017, $p < .01$) and product quantity (b = -.024, $p < .01$), in support of H_{4a} and H_{4b}. When buying on mobile devices, customers buy cheaper and fewer items than they would through other online channels. We also find that seller quality significantly weakens the negative effect of the mobile transaction on product price (b = .006, $p < .05$) and product quantity (b = .012, $p < .01$), which supports H_{5a} and H_{5b}. Similarly, product risk significantly strengthens the negative effects of a mobile transaction on product price (b = -.011, $p < .01$) and product quantity (b = -.017, $p < .01$). These results support both H_{6a} and H_{6b}.

Robustness analyses

To test the robustness of the results and identify the optimal mobile shopping ratio, such that customers provide the highest sales numbers, we reestimated Equation 2 with a level-in-level approach instead of a first differencing approach. The results are consistent with our findings with first differencing (see Appendix A). On average, the best sales can be obtained if customers' mobile shopping ratio is 38%. A customer who chooses mobile devices once every three times he or she shops online thus is more profitable than those who shop on their mobile devices less or more frequently.

As a sensitivity check, we also reestimated Equation 4 at the transaction level instead of the customer level (see Appendix B). The results are consistent with our main findings, so our results are robust across different levels of analysis.

Study 2: Effects of Mobile Traffic on Financial Performance

To generalize our understanding of the mobile channel expansion strategy beyond the customer and transaction levels, we conducted Study 2 at the firm level of analysis. In doing so, we use *mobile traffic ratio*—the proportion of the customer's visits through mobile devices relative to total online visits—as a parallel construct to the mobile shopping ratio from Study 1. The use of this mobile traffic ratio adds two major strengths. First, we extend our Study 1 findings by assessing the effect of a mobile channel expansion strategy across various industries in which firms generate revenues from selling advertising placements, using pay-per-click or pay-per-view models, instead of selling offerings directly to consumers through their website. As a result, the mobile traffic ratio functions as an umbrella measure of mobile channel expansion. Second, this umbrella measure of mobile channel expansion then can be applied to various industries, so we can assess investors' and stock markets' expectations of the mobile strategy and offers insights into external valuations of mobile channel expansion. Consistent with Study 1, we demonstrate that firms with a moderate mobile traffic ratio achieve higher levels of stock returns than those with either lower or higher mobile traffic ratio levels (inverted U-shaped effect). We illustrate this conceptual model in Figure 2.

Main Effect of Mobile Traffic Ratio on Financial Performance

Increasing the mobile traffic ratio, from low to moderate levels, should allow firms to enhance their financial performance by expanding the size of the customer base, but an excess of mobile traffic may harm this financial performance, due to the lower conversion rates that mark mobile devices (Haan et al. 2015). The marginal benefits of increased mobile viewership likely diminish, but the costs of lower mobile conversions or add-to-cart rates grow at an increasing rate, so the net performance effect of the mobile traffic ratio should exhibit an inverted U-shape.

At lower levels of mobile traffic, performance will improve with the mobile traffic ratio, because launching a mobile channel attracts customers who have access only on smartphones or who want to expand their visits, beyond their usual online activity. For example, the ubiquitous nature of mobile devices attracts people who would only visit sites on their smartphones (e.g., on-the-go users, mobile-only customers), so its very presence increases the amount of both unique and total traffic (McGrane 2013). Mobile device users can search for the product/service information or location of the business, anywhere and anytime, so they likely become more familiar with the firm and its products. Moreover, visits made on mobile devices often prompt customers to perform related online and offline actions, which leads to improved business outcomes. For example, customers who conduct mobile searches often share information, spread word of mouth in person, make purchases, and visit a physical store (The Nielsen Company 2013), which ultimately should improve the firm's financial performance.

However, as the mobile traffic ratio increases beyond a certain threshold, the benefits of an increased customer base will be offset by a lower sales conversion rate on mobile devices. The mobile interface often fails to convert customers, because they are concerned with mobile security (*Fortune* 2014) and want to gather more detailed information on their desktops (Ghose and Han 2011). For example, the smaller screens of mobile devices may hinder firms from offering effective banner advertisements and product displays. As a result, "most ecommerce sales are generated via websites (mostly desktop sites) compared with apps" (eMarketer 2015). Because the mobile device functions as a research platform, instead of a purchasing platform, the firm loses an opportunity to monetize its online traffic when most visitors come through mobile devices. In summary, an increased mobile traffic ratio may result in a small increment in channel expansion benefits, accompanied by a large loss in sales, producing an inverted U-shaped relationship with financial performance.

> **H_7:** At lower levels, the firm mobile traffic ratio positively affects financial performance, then after a critical point, the firm mobile shopping ratio negatively affects firm performance (i.e., inverted U-shaped relationship between mobile traffic ratio and financial performance).

Firm-Level Moderators of the Effect of the Mobile Traffic Ratio on Financial Performance

Operating efficiency. Operating efficiency refers to a firm's capability to earn profits. Firms with high operating efficiency have enough resources to build more effective mobile interfaces and network capacity, so they are better equipped to analyze mobile traffic patterns and customers' distinctive behavior, such that those firms can monetize the high mobile traffic they attract more effectively. Yet firms with low operating efficiency often lack sufficient resources that would enable them to conduct research on mobile traffic data or produce real-time traffic reports, so high levels of mobile traffic may add more complexities and become a burden instead of generating additional revenue. In line with this view, "cost and efficiency are critical in determining the winner, because mobile apps enable consumers to make instant price comparisons across channels" (Brynjolfsson, Hu, and Rahman 2013, p. 27). Firms with high operating efficiency likely achieve greater levels of mobile conversions, even when the mobile traffic ratio is high, which would weaken the cost mechanism and make the inverted U-shape flatter. Thus we propose that operating efficiency mitigates the negative effect of the mobile traffic ratio in such a way that the curve of the inverted U-shaped relationship between the mobile traffic ratio and financial performance grows flatter.

> **H_{8a}:** Operating efficiency moderates the relationship between the mobile traffic ratio and financial performance; the inverted U-shaped relationship is suppressed in firms with high operating efficiency.

Website cognitive load. Website cognitive load refers to the degree of mental effort needed to use a particular website. It affects "how easily users find content and complete tasks" (Whitenton 2013). Depending on the type of offerings, each website creates an inherent cognitive load that is required for information processing and decision making. For example, customers may be more careful and spend more time per page when they shop for offerings associated with higher perceived risk (e.g., computers, loan services) or need to comprehend complex information that requires a great deal of concentration (e.g., researching financial investments). In contrast, they tend to spend less time per page when they shop for offerings associated with lower perceived risk (e.g., apparel, non-durable goods) or process information that does not require close attention to details (e.g., reading cartoons). If the firms ensure that their websites demand a low cognitive load, they also might tend to offer products or information that customers use habitually, so customers do not need the full product information. These firms then can easily convert the mobile transaction into sales, which ultimately enhances financial performance. In contrast, when firms provide offerings or information that requires much more time to process, customers tend to delay their final purchase decision until they can access more reliable channels, such as personal computers. As such, firms with high cognitive load are more likely to lose conversion opportunities as mobile traffic increases than are those with low cognitive load. In summary, website cognitive load likely accentuates the negative effect of the mobile traffic ratio, such that the curvature of the inverted U-shaped relationship between mobile traffic ratio and financial performance is steeper.

H_{8b}: Website cognitive load moderates the relationship between the mobile traffic ratio and financial performance in such a way that the inverted U-shaped relationship becomes amplified in firms with high website cognitive load.

Online store presence. An online store presence indicates whether the firm generates any revenue from online monetary transactions that require an online shopping cart. Some retailers and manufacturers (e.g., Walmart, Apple) generate partial or total revenues from direct online sales; others do not sell their offerings directly to consumers but rather earn revenues from selling advertising space (e.g., pay-per-click, pay-per-view), as on search engines (e.g., Yahoo, Bing), or only from traditional distribution channels. The effect of the mobile traffic ratio on business performance may vary with the presence or absence of an online store, because of the fundamental differences in the revenue model. A higher mobile traffic ratio will be more valuable to firms that do not depend on online stores, because they can capitalize on the sheer amount of traffic; in contrast, higher mobile traffic does not necessarily translate into increased profit for firms with online stores, unless customers make purchases. As the cost mechanism of the lower conversion rate becomes stronger, we expect that the presence of an online store mitigates the negative effect of the mobile traffic ratio, so the curvature of the inverted U-shaped relationship between the mobile traffic ratio and financial performance is flattened.

H_{8c}: Online store presence moderates the relationship between the mobile traffic ratio and financial performance in such a way that the inverted U-shaped relationship is suppressed in firms with online stores.

Data

Our sampling frame is a list of firms from comScore Media Metrix Multiplatform, because this data set provides detailed information about digital audience behavior across multiple online channels (mobile, personal computers). The comScore data provide monthly reports on online traffic and usage information (e.g., unduplicated audience sizes, demographic composition) for more than 300,000 digital media entities. We merged these data with information from the Center for Research in Security Prices (CRSP) and COMPUSTAT to evaluate the effect of mobile traffic on stock returns and understand which firm factors leverage these effects. Merging these data sets yielded a pooled, cross-sectional time-series panel of 1,301 observations of 205 publicly traded U.S. firms that achieved the highest website traffic over a seven-month period (June–December 2014).

Measures

Financial performance. We measure firm performance with the four-factor alpha abnormal return, calculated as the intercept term of the Carhart four-factor model[1] (Carhart 1997):

$$R_{it} - R_{rf,t} = \alpha_i + \beta_i(R_{mt} - R_{rf,t}) + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{it},$$

where R_{it} is the stock return for firm i at time t, $R_{rf,t}$ is the risk-free rate of return in period t, R_{mt} is the average market rate of return in period t, SMB is the return on a value-weighted portfolio of small stocks minus the return of big stocks, HML is the return on a value-weighted portfolio of high book-to-market stocks less the return on a value weighted portfolio of low book-to-market stocks, UMD is the average return on two high prior return portfolios less the average return on two low prior return portfolios, and ε_{it} captures additional abnormal (excess) returns associated with period t. The measure of financial performance of company i is measured by the intercept term α_i, which captures the abnormal return associated with firm i.

Mobile traffic ratio. The mobile traffic ratio is the percentage of mobile traffic relative to total online traffic, including personal computers (i.e., number of mobile visits divided by the number of total online visits), provided by comScore.

Moderating variables. A firm's *operating efficiency* is operationalized as the annual return on assets, calculated as the net income divided by total assets. *Website cognitive load* is measured by the average length of time (minutes) customers spent viewing a webpage, which represents the amount of time a customer views one webpage in the firm's website, regardless of which device he or she used. A longer time spent per page indicates that the website demands a higher cognitive load. *Online store presence* is a dummy variable coded as 1 when the website has a shopping cart and 0 otherwise. This variable was manually coded by two independent researchers who evaluated the presence of an online shopping cart by visiting the websites of all firms in the sample (alpha = .92, disagreement resolved through discussion).

Control variables. To account for firm- and industry-level factors, we control for total traffic, website popularity, firm size, firm revenue, industry competitiveness, industry dynamism, and industry growth. Total traffic equaled the total amount of customer online traffic, including both mobile and personal computers. Website popularity was measured as the number of pages a customer views per visit. Firm size reflects the firm's total assets, and firm revenue was measured as a firm's sales revenue, obtained from COMPUSTAT. Industry competitiveness was

[1] These data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

operationalized as a Herfindahl index, measured as the sum of the squares of the market shares of the firms within the same standard industrial code (SIC). We measured industry dynamism as the standard deviation of sales of all firms with the same four-digit SIC code. Industry growth reflects the autoregression coefficient of industrial sales within the same four-digit SIC code. In Table 2, we describe the constructs, definitions, measures, and data sources. In Panel C of Table 3, we summarize the descriptive statistics for the variables we used in Study 2.

Model specification

We now discuss the regression model for Study 2. Our unit of analysis is at the firm (i)/month (t) level. Some key variables are time-invariant (e.g., online store presence, operating efficiency), so a fixed effect model is not appropriate. To control for the time effect, we include month dummies in the regression model. In line with prior studies (Hayward 2002; Luo, Kanuri, and Andrews 2014), we consider the following estimation equation:

$$\begin{aligned}\text{Financial Performance}_{it} = {} & \text{Financial Performance}_{it-1} + \gamma_0 + \gamma_1\text{MobileTrafficRatio}_{it} + \\ & \gamma_2\text{MobileTrafficRatio}_{it}{}^2 + \gamma_3\text{OperatingEfficiency}_i + \gamma_4\text{WebsiteCognitiveLoad}_{it} + \\ & \gamma_5\text{OnlineStorePresence}_{\,i} + \gamma_6\text{MobileTrafficRatio}_{it} \times \text{FirmEfficiency}_i + \\ & \gamma_7\text{MobileTrafficRatio}_{it} \times \text{WebsiteCognitiveLoad}_{it} + \gamma_8\text{MobileTrafficRatio}_{it} \times \\ & \text{OnlineStorePresence}_{\,i} + \gamma_9\text{MobileTrafficRatio}_{it}{}^2 \times \text{OperatingEfficiency}_i + \\ & \gamma_{10}\text{MobileTrafficRatio}_{it}{}^2 \times \text{WebsiteCognitiveLoad}_{it} + \gamma_{11}\text{MobileTrafficRatio}_{it}{}^2 \times \\ & \text{OnlineStorePresence}_{\,i} + \gamma_{12}\text{Controls}_{it} + \varepsilon_{it}\,, \qquad (7)\end{aligned}$$

where i is the company index, and t refers to the month (t = 1, …, 7). The controls were the firm's total traffic, website popularity, firm size, firm revenue, industry competitiveness, industry dynamism, and industry growth. We also included lagged financial performance, to capture the dynamic effect (Steenkamp and Fang 2011).

Results and discussion

As shown in Model 1 of Table 6, we find support for H_7, because the mobile traffic ratio has a significant first-order effect (b = .235, $p < .05$) and a significant second-order effect (b = -.313, $p < .01$) on firm performance. The mobile traffic ratio thus has an inverted U-shaped effect on the firm's performance; when the ratio of mobile traffic reaches to a certain value, increasing mobile traffic further does not translate into a higher stock return.

The estimation results of the moderation hypotheses are in Model 2 of Table 6. In support of H_{8a}, we find a significant positive interaction effect of operating efficiency and the second-order term of the mobile traffic ratio on financial performance (b = .530, $p < .05$), such that the inverted U-shaped curve weakens. The significant, negative interaction effect of operating efficiency with the second-order term of the mobile traffic ratio on financial performance (b = -.338, p < .05) also supports H_{8b}. However, we do not find support for H_{8c}, because the second-order term of the mobile traffic ratio on financial performance is not significant (b = .351, *n.s.*).

Discussion

To the best of our knowledge, this article is the first to identify the dark side of mobile channels. Despite the predictions that "By 2014 mobile internet will overtake desktop internet usage for shopping" (*The Economist* 2012), our findings suggest that firms still can reap the most benefits when customers use mobile devices at a moderate level for their shopping and browsing. This outcome might explain why researchers have found that mobile channels can either complement or cannibalize sales from existing channels (Xu et al. 2014).

Theoretical Implications

Assessing mobile's share in online sessions, we examine the effect of a mobile channel expansion strategy in two studies. In Study 1, we show how the *purchase occasion* conducted through mobile devices, relative to total online purchase occasions, affects sales by evaluating the mobile shopping ratio and mobile transaction ratio. Shoppers that rely more on mobile devices generate a greater level of sales, because they tend to buy more frequently (increased transaction frequency), but they generate less sales, because they spend less (decreased transaction spending) on each purchase. Due to these trade-offs, the overall effect of mobile shopping on customer sales is an inverted U-shape. The positive effect of mobile shopping on transaction frequency gets enhanced by seller quality but suppressed by product risk; the negative effect of mobile shopping on transaction spending is alleviated by seller quality but aggravated by product risk. Our findings are robust at multiple levels of analysis and across different model specifications (first-differencing, level-in-level).

To identify the mechanism by which mobile shopping harms transaction spending, we consider mobile transactions and find that customers purchase not only fewer (lower quantity) items but also cheaper (lower price) products on mobile devices than on other digital devices (e.g., personal computers). Consistent with the customer-level analysis, the negative effect of mobile shopping on product price and product quantity is suppressed by seller quality but aggravated by product risk.

In Study 2, we study customers' *visits* using mobile devices, relative to total online visits, and reveal that the mobile traffic ratio exhibits an inverted U-shaped relationship with stock returns. Such negative effects are mitigated in firms with high operating efficiency, low website cognitive load, or absence of online stores. Some academics have cast doubt on the economic value of a mobile expansion strategy (Koenigstorfer and Groeppel-Klein 2012), but our multilevel analysis across the transaction, customer, and firm levels reveals that an excessive emphasis on mobile channel expansion can be counterproductive with regard to gains in performance metrics, including customer sales and stock returns.

Managerial Implications

To provide managerial guidance, we graphically illustrate the observed relationships between the mobile ratio and performance metrics. To compare the mobile channel's effect across customer and firm levels, we first depict the customer-level relationship between the mobile shopping ratio and customer sales. Consistent with the findings of Study 1, Panel A of Figure 3 shows that the highest customer sales would be achieved when the mobile shopping ratio is about 38%, meaning that customers are most profitable when they choose mobile devices about once out of every three online shopping occasions. Similarly, our firm-level model in Panel B shows that the average point where the mobile traffic ratio appears to have negative consequences for stock returns is at 51%, so if firms attract more than half their traffic from mobile devices, negative effects arise. We suggest managers closely monitor this ratio and avoid overextending into mobile channels; instead they should seek to maintain a balance across different online channels.

We also illustrate how the optimal mobile traffic ratio shifts with different moderators in Figure 4, by depicting the observed relationships between the mobile traffic ratio and financial performance, all other things being equal, at high and low levels of the moderators (one standard deviation above or below the mean). In Panel A, in firms with low operating efficiency, the negative effect of mobile traffic becomes more salient, so stock returns start to diminish at 25% of the mobile traffic ratio. In firms with high operating efficiency, the positive effect of the mobile traffic ratio on stock returns endures for longer. Thus, improving operating efficiency would be an advisable strategy for firms, as it not only directly contributes to the bottom line, but increases the returns from mobile traffic.

If firms' websites impose low cognitive loads on customers, the negative effect of mobile traffic on stock returns becomes weaker and does not set in until the mobile traffic ratio reaches 64% (Panel B). Thus, it is advisable that firms develop websites that do not require much cognitive effort from consumers to navigate. Firms could try alternative website versions and easily measure consumers' cognitive load by examining the statistics on the length of time spent per page before settling on the final website design and functionality.

The results of this research also show that displaying indications of seller quality would help firms. Providing seller quality indications could help reduce customers' cognitive load and aid the decision-making especially when it comes to risky products. Combining our finding on the moderating role of website cognitive load and the importance of seller quality, when developing mobile websites or applications, companies would be wise to prominently display some indications of seller quality such as consumer reviews. Displaying seller quality indications could potentially lower the customers' cognitive load and the perceptions of product risk.

When firms do not have online stores, performance peaks much later, at about 65% (Panel C). Therefore, top managers should recognize the characteristics of their businesses and websites, then find an ideal mobile traffic ratio instead of blindly chasing a "mobile-first" approach (Bain & Company 2015). Developing and implementing the mobile shopping channel should be done thoughtfully and in ways that would minimize the limitations of the channel. Many firms in a rush to add a mobile channel assume that their online websites will work just as well in a mobile interface and do not adapt to it in any way. This is not an ideal strategy, as a mobile shopper cannot as easily as an online shopper scroll or navigate to other pages; all of these actions would increase website's cognitive load for a mobile shopper. Our results show that not optimizing the website for a mobile channel will lead to the negative effects of mobile traffic on stock returns setting in much sooner, since websites or applications not specifically developed for a mobile device will not address the limitations of this channel. Overall, managers should strive to develop mobile websites where customers could identify a product and complete their purchase in as few clicks as possible. Another important aspect to consider is the type of commerce (B2C vs. C2C), as it significantly impacted all of the dependent variables in Study 1 (a control variable in the analysis).

Limitations and further research directions

Our paper has several limitations that offer directions for research. First, we did not capture the psychological process underlying mobile shopping at the individual customer level. Additional studies might rely on lab or field experiments to uncover the mechanisms associated with the negative and positive effects of mobile shopping on spending and frequency. Second, it would be valuable to investigate interactions with the presence of offline stores, because it appears “mobile [is] extending the longevity of brick-and-mortar stores” (*Forbes* 2015a). Studies could consider the impact of mobile shopping on offline shopping, and vice versa. Third, further research might build on this study to understand how consumer characteristics (e.g., cultural background) affect mobile shopping behaviors. It would be interesting to examine if and how the effectiveness of mobile channel expansion varies across emerging versus developed countries.

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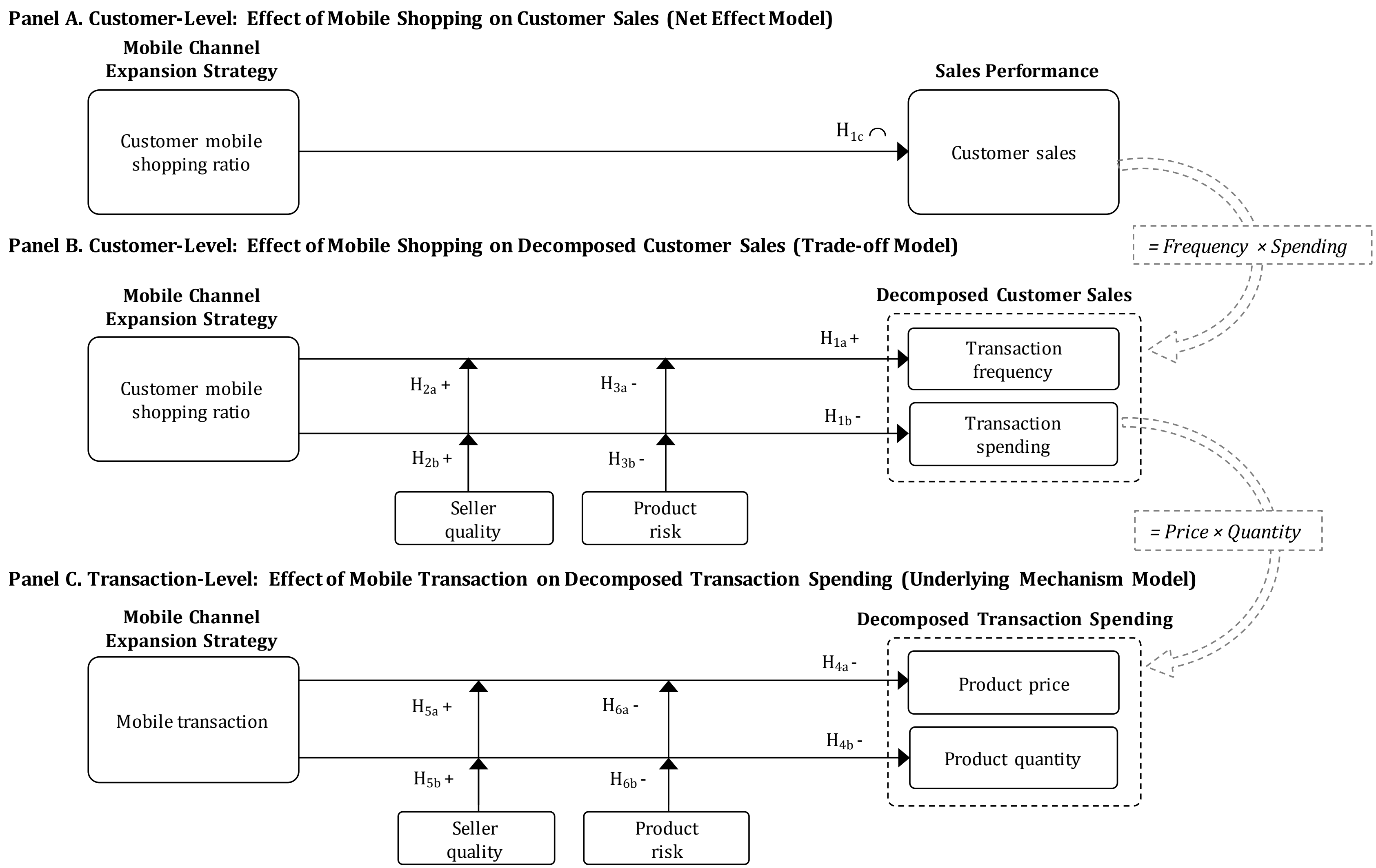
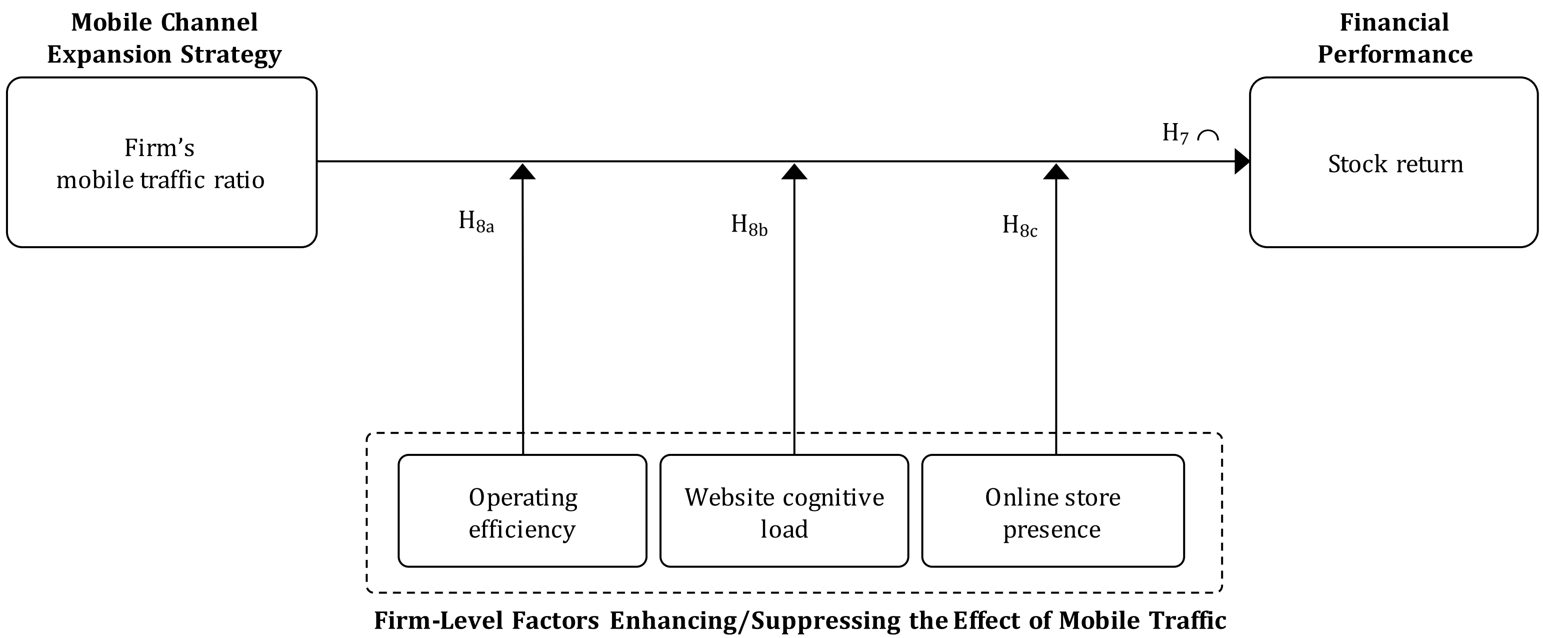
Figure 1

STUDY 1: CUSTOMER- AND TRANSACTION-LEVEL MODELS TO DECOMPOSE THE EFFECTS OF MOBILE SHOPPING ON CUSTOMER SALES



Notes: Panels A and B were tested on 14,208 valid customers who made purchases on a leading online shopping platform over two years (June 2012 to June 2014). Panel C was tested on 218,330 transactions that those customers made on the same shopping platform.

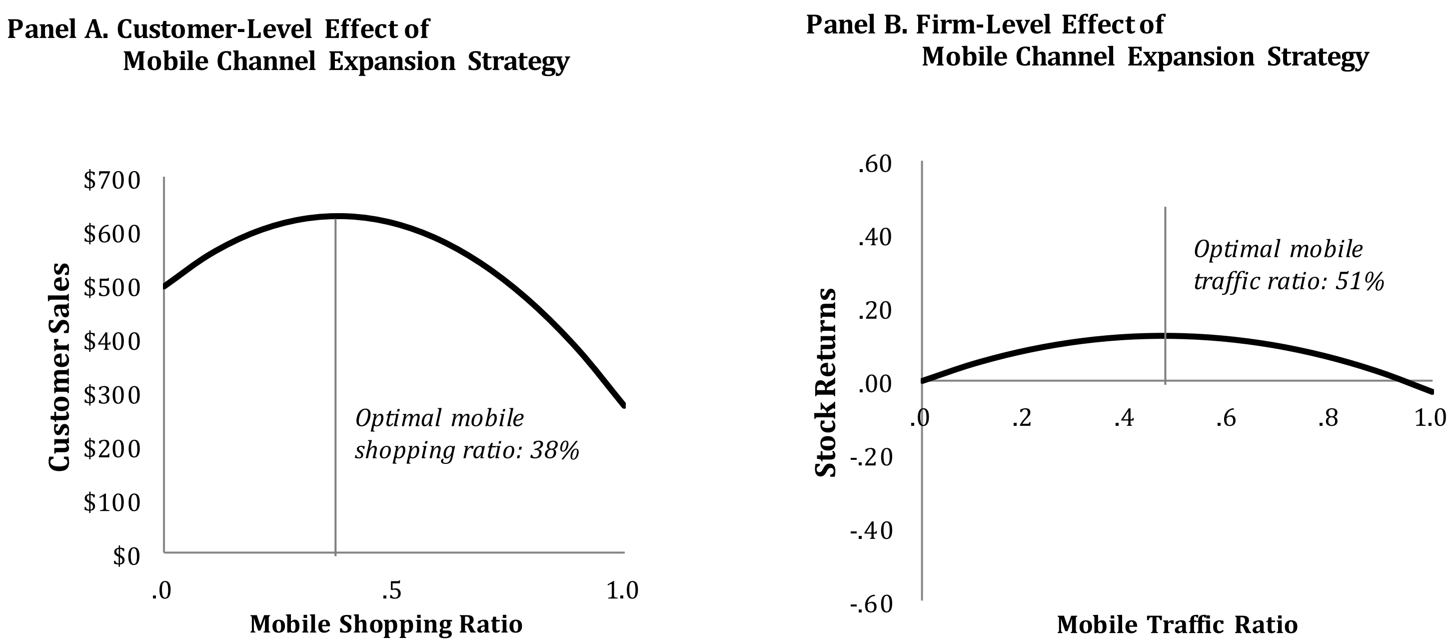
Figure 2
STUDY 2: FIRM-LEVEL MODEL ON THE EFFECT OF MOBILE TRAFFIC ON FINANCIAL PERFORMANCE



Notes: This model was tested on 205 publicly traded U.S. firms over a seven-month period (from June 2014 to December 2014).

Figure 3

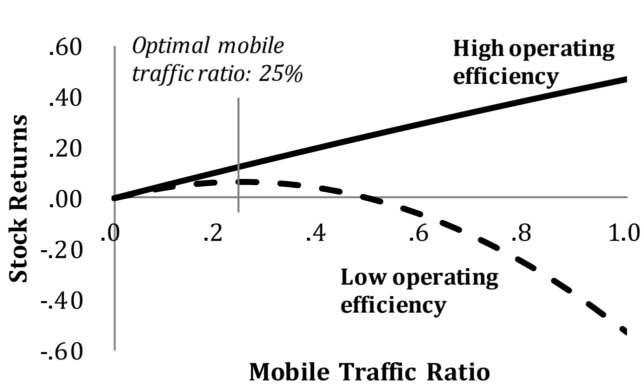
CUSTOMER- AND FIRM-LEVEL PERFORMANCE EFFECTS OF MOBILE CHANNEL EXPANSION STRATEGY



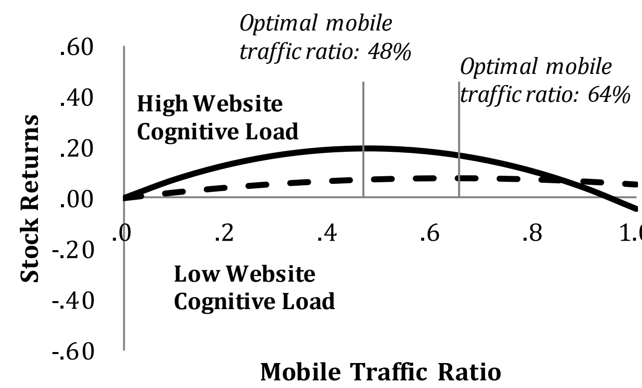
Notes: Panel A shows the observed relationships between mobile shopping ratio and sales performance at the average level of moderators, using customer-level data of 14,208 valid customers who made purchases on a leading online shopping platform over two years (June 2012 to June 2014). Panel B shows the observed relationships between mobile traffic ratio and financial performance at the average level of moderators, using firm-level data of 205 publicly traded U.S. firms over a seven-month period (from June 2014 to December 2014).

Figure 4
FIRM-LEVEL MODERATORS OF THE EFFECT OF MOBILE CHANNEL EXPANSION STRATEGY ON FIRM PERFORMANCE

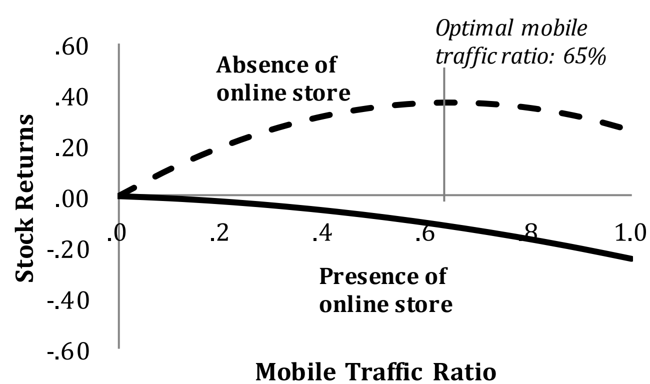
Panel A. Moderating Effect of Operating Efficiency



Panel B. Moderating Effect of Website Cognitive Load



Panel C. Moderating Effect of Online Store Presence



Notes: Panel A, B, and C show the observed relationships between mobile traffic ratio and financial performance, all other things equal, at low (one standard deviation below the mean) and high (one standard deviation above the mean) levels of the moderators. The graphs are based on firm-level data of 205 publicly traded U.S. firms over a seven-month period (from June 2014 to December 2014).

Table 1
LITERATURE REVIEW ON MOBILE CHANNELS

Authors	Research Context	Antecedents of Mobile Shopping	Outcomes of Mobile Shopping	Findings
Brasel and Gips (2014)	Lab experiments of 56 students at an east coast university	N/A	• Perceived psychological ownership • Endowment effect	Touchscreen interfaces, such as mobile devices, increase perceived psychological ownership, which magnifies the endowment effect. The positive effect of touch interfaces on perceived product ownership is stronger for products high in haptic importance and interfaces that are owned.
Ghose, Goldfarb, and Han (2013)	Microblogging service company in South Korea	N/A	N/A	Top ranked posts in the mobile setting are more likely to be clicked on mobile phones than those in the PC setting. Stores located geographically close to a user are more likely to be clicked on mobile phones.
Kleijnen, de Ruyter, and Wetzels (2007)	Survey of 375 respondents who had an affinity with mobile brokerage services in the Netherlands	• Time convenience • User control • Service compatibility • Perceived risk • Cognitive effort	N/A	Time convenience, user control, perceived risk, and cognitive effort are antecedents of perceived value of mobile channel, which in turn affects the intentions to use mobile services. Time consciousness moderates the relationship between the antecedents and perceived value of mobile channel.
Ko, Kim, and Lee (2009)	Online survey of 511 users of a mobile Internet service in Korea	• Usefulness • Enjoyment • Ease of use • Instant connectivity	N/A	Consumers' perceived usefulness, enjoyment, ease of use of mobile phones improve their perceived value, which in turn promotes the intention to adopt mobile shopping. Instant connectivity reduces the perceived value of mobile shopping.
Koenigstorfer and Groeppel-Klein (2012)	Survey of 169 participants	• Consumer's tendency to be a technology pioneer • Desire for social contact • Technology optimism • Demographic factors	N/A	Mobile Internet services are more likely to be chosen by (1) male consumers with a tendency to be a technology pioneer, (2) female consumers with a low desire for social contact, and (3) young consumers with high technology optimism.
Lu and Su (2009)	Online survey of 382 respondents in Taiwan	• Enjoyment • Ease of access • Usefulness • Compatibility • Anxiety	N/A	Customers' intention to mobile shop is increased by their enjoyment, usefulness, and compatibility of mobile shopping but decreased by their anxiety over mobile shopping services.
Shankar et al. (2010)	Theoretical discussion	• Need for social networking (Millennials) • Need for productivity and convenience (Road Warriors)	• Customer loyalty	Consumers with a high need for social networking or convenience are more likely to choose a mobile interface. Retailers can use mobile marketing as a means to increase customer loyalty.
Sultan, Rohm, and Gao (2009)	Surveys of 169 students in the United States and 215 students in Pakistan	• Risk acceptance • Personal attachment	N/A	Customers' risk acceptance and personal attachment to mobile phones foster their mobile activities (e.g., providing information, sharing content, accessing content), which makes those customers more likely to accept mobile marketing.
Wang, Malthoues, and Krishnamurthi (2015)	Internet-based grocery retailer in the United States that launched a mobile app promotion campaign in 2012	• Customer's habitual needs • Customer's tenure • Demographic factors	• Order rate • Order size	Mobile shopping has a positive effect on order rate but no effect on order size. For low spenders, the effects of mobile shopping on order size and the order rate are enhanced. Mobile shoppers are more likely to purchase habitual products vs. products that they do not have a history of purchasing.
Xu et al. (2014)	Introduction of the Fox News mobile app	N/A	N/A	Introduction of a mobile app increases the demand at corresponding mobile news website for consumers with (1) greater appreciation for dense news content, (2) higher propensity for a particular political view, and (3) fewer time constraints.

Table 2
CONSTRUCTS, DEFINITIONS, AND OPERATIONALIZATIONS

Constructs	Definitions	Operationalizations
Study 1		
Customer-Level Variables (Panel A and B of Figure 1)		
Customer mobile shopping ratio	Thee degree to which customers have adopted a firm's mobile channel for shopping	The percentage of orders that a customer placed on a mobile channel relative to the total online channels [customer].
Customer sales	Customer's total shopping expenditures	Total amount of money a customer spent on the shopping platform through all online channels [customer].
Transaction frequency	Order frequency of the customer	The number of orders that the customer has placed through all online channels [customer].
Transaction spending	Customer's shopping expenditures per order	Average expenditure per transaction (equal to customer sales divided by transaction frequency) [customer].
Transaction-Level Variables (Panel C of Figure 1)		
Mobile transaction	Whether the customer chooses mobile devices to place an order	Dummy variable coded as 1 if the order was placed on mobile devices; 0 otherwise (e.g., personal computers) [transaction].
Product price	Average price of the product in a single order	Average unit price of the product in a transaction. We log-transformed this measure to alleviate the skewness [transaction].
Product quantity	Quantity of products in a single order	The number of products ordered in the transaction. We log-transformed this measure to alleviate the skewness [transaction].
Prior stage mobile ratio	Customer's preference for mobile transactions	Customer's percentage of mobile orders relative to total orders in the previous time period [transaction].
Transaction- and Customer-Level Variables (Panel A, B, and C of Figure 1)		
Seller quality	Customers' perceptions of the seller involved in the trasaction	Customer rating toward the seller involved in the transactions [transaction]. The average customer rating of sellers aggregated to the customer level [customer].
Product risk	Customers' perceptions of uncertainty and adverse consequences resulting from a purchase	Dummy variable coded as 1 when the customer purchases a risky product in each transaction [transaction]. The percentage of orders containing risky products over all orders aggregated to the customer level [customer].
Gender	Gender of the customer	Dummy variable coded as 1 when a customer is female; 0 otherwise [transaction, customer].
Age	Age of the customer	Self-reported age of the customer [transaction, customer].
Membership duration	The length of time a customer has been on the site	The number of months since the customer joined the website [transaction, customer].
Seller popularity	Size of the seller	The historical cumulative sales of the seller in a given transaction [transaction]. The average historical cumulative sales of all sellers aggregated to the customer level [customer].
Product popularity	Best-selling product	The historical cumulative sales of the products that the customer has ordered [transaction]. The average historical cumulative sales of all products aggregated to the customer level [customer].
Type of commerce	The extent to which a customer uses a B2C vs. C2C platform	Dummy variable coded as 1 when the transaction is completed on a B2C platform and 0 on a C2C platform [transaction]. The percentage of orders placed on the B2C platform by the customer [customer].
City	Geographical location of the customer	A set of dummy variables that capture different geographical districts [transaction, customer].
Time	Distinctive data time window	A set of dummy variables that capture different time windows [transaction, customer].
Study 2		
Firm-Level Variables (Figure 2)		
Financial performance	Firm's monthly abnormal stock return	Constant term of Fama-French four-factor model (CRSP) [firm].
Mobile traffic ratio	Thee degree to which customers have adopted a firm's mobile channel for website visits	The percentage of mobile traffic relative to the total online traffic including personal computers (comScore) [firm].
Operating efficiency	Capability of earning profit	The net income divided by the total assets (COMPUSTAT) [firm].
Website cognitive load	The degree of customers' mental efforts needed to use a particular website	Average length of time (in minutes) customers spent viewing a webpage (comScore) [firm].
Online store presence	Whether a firm generates revenue from online monetary transaction	Coded as 1 when the website has a shopping cart and 0 otherwise (each firm's website) [firm].
Total traffic	The size of the total online traffic	Firm's total amount of customer online traffic, including both mobile and personal computers (comScore) [firm].
Website popularity	Customer's interest in the website	The number of pages a customer views per visit (comScore) [firm].
Firm size	The size of the firm	A firm's total assets (COMPUSTAT) [firm].
Firm revenue	The revenue of the firm	A firm's sales revenue (COMPUSTAT) [firm].
Industry competitiveness	Level of competition in a particular industry	Herfindahl index, measured as the sum of the squares of the market shares of the firms within the same SIC code industry (COMPUSTAT) [firm].
Industry dynamism	The degree of turbulence within an industry	Standard deviation of sales of all firms with the same four-digit SIC code (COMPUSTAT) [firm].
Industry growth	Rate of sales revenue growth within an industry	The autoregression coefficient of industrial sales within the same four-digit SIC code (COMPUSTAT) [firm].

Notes: Brackets represent the level of analysis. Parentheses represent the data source of variables in Study 2. Study 1 data come from a leading online shopping platform firm.

Table 3
DESCRIPTIVE STATISTICS AND CORRELATIONS

Panel A. Study 1 Customer-Level Data

Variables	Mean	SD	Correlation Matrix											
			1	2	3	4	5	6	7	8	9	10	11	12
1. Customer sales	570.704	1,232.726	1.000											
2. Transaction frequency	5.532	5.861	.434	1.000										
3. Transaction spending	105.443	120.848	.538	-.018	1.000									
4. Mobile shopping ratio	.081	.225	-.002	.005	-.019	1.000								
5. Seller quality	.123	.115	.077	.028	.147	.024	1.000							
6. Product risk	.380	.357	-.006	-.038	.041	-.038	-.038	1.000						
7. Gender	.841	.366	.012	.027	.009	.042	.043	.026	1.000					
8. Age	31.327	5.685	.009	-.017	.030	-.027	.064	-.081	-.095	1.000				
9. Membership duration	41.155	12.199	-.005	-.019	.023	.011	.036	-.031	-.066	.140	1.000			
10. Seller popularity	255,394.400	414,031	.026	.111	-.036	-.004	-.171	-.225	-.006	-.037	-.031	1.000		
11. Product popularity	912.784	1,354.138	-.029	.038	-.102	-.016	-.070	-.025	-.044	-.029	-.013	.209	1.000	
12. Type of commerce (B2C vs. C2C)	.586	.372	.041	.016	.092	-.020	-.006	.146	-.099	.073	.029	.152	.114	1.000

Panel B. Study 1 Transaction-Level Data

Variables	Mean	SD	Correlation Matrix											
			1	2	3	4	5	6	7	8	9	10	11	12
1. Product price	53.198	74.919	1.000											
2. Product quantity	5.532	20.569	-.115	1.000										
3. Mobile transaction	.072	.259	-.037	.005	1.000									
4. Seller quality	.125	.156	.079	-.038	.021	1.000								
5. Product risk	.389	.487	.175	-.049	-.040	-.052	1.000							
6. Gender	.852	.355	-.003	.009	.035	.033	.026	1.000						
7. Age	31.245	5.640	.037	-.021	-.026	.068	-.061	-.088	1.000					
8. Membership duration	40.885	11.981	.009	-.013	.011	.036	-.023	-.060	.143	1.000				
9. Seller popularity	286,240	613,559	.042	-.040	-.008	-.153	-.242	-.044	-.034	-.033	1.000			
10. Product popularity	853.154	1,924.871	-.076	-.040	.009	-.043	-.051	-.035	-.023	-.014	.214	1.000		
11. Type of commerce (B2C vs. C2C)	.590	.492	.261	-.158	-.026	-.051	.120	-.077	.053	.016	.183	.108	1.000	
12. Prior stage mobile ratio	.014	.092	-.013	-.001	.351	.020	-.015	.032	-.007	.013	-.012	-.004	-.021	1.000

Panel C. Study 2 Firm-Level Data

Variables	Mean	SD	Correlation Matrix											
			1	2	3	4	5	6	7	8	9	10	11	12
1. Firm performance	.001	.006	1.000											
2. Mobile traffic ratio	.421	.195	.024	1.000										
3. Operating efficiency	.028	.180	-.142	.037	1.000									
4. Website cognitive load	2.667	11.095	-.040	-.037	-.069	1.000								
5. Online store presence	.594	.491	-.021	-.022	.173	-.065	1.000							
6. Total traffic	221,618.700	1,112,897	-.002	-.020	.053	.006	-.143	1.000						
7. Website popularity	7.103	4.874	-.005	-.179	.132	-.155	.194	.044	1.000					
8. Firm size	86,464.440	307,498.100	-.021	-.209	.000	-.017	-.201	.013	.226	1.000				
9. Firm revenue	26,840.160	49,605.350	-.010	-.002	.094	.067	.057	.065	.099	.330	1.000			
10. Industry competitiveness	.773	.194	.012	-.081	-.112	-.024	-.163	.076	.053	.060	-.195	1.000		
11. Industry dynamism	.121	.075	-.015	.030	-.117	-.011	-.118	.079	-.165	-.179	-.225	-.191	1.000	
12. Industry growth	.234	.246	.009	.002	-.108	.032	-.103	.106	-.052	-.176	-.034	.039	.320	1.000

Table 4

STUDY 1: CUSTOMER-LEVEL ANALYSIS RESULTS ON THE EFFECT OF MOBILE SHOPPING RATIO ON CUSTOMER SALES AND DECOMPOSED CUSTOMER SALES

Dependent Variable		**Customer Sales**		**Transaction Frequency**			**Transaction Spending**	
		Model 1		**Model 2**	**Model 3**		**Model 4**	**Model 5**
		Net Effect Model (Inverted U-Shaped)		**Main Effect (Linear)**	**Main and Interaction**		**Main Effect (Linear)**	**Main and Interaction**
Main Effects								
Mobile shopping ratio		.218 (.018)**	$\mathbf{H_{1a}}$	.033 (.005)**	.027 (.008)**	$\mathbf{H_{1b}}$	-.014 (.006)*	-.014 (.009)
Mobile shopping ratio^2	$\mathbf{H_{1c}}$	-.210 (.017)**						
Moderating Effects								
Mobile shopping ratio × Seller quality			$\mathbf{H_{2a}}$		.024 (.007)**	$\mathbf{H_{2b}}$		.016 (.007)*
Mobile shopping ratio × Product risk			$\mathbf{H_{3a}}$		-.016 (.006)**	$\mathbf{H_{3b}}$		-.015 (.007)*
Control Variables								
Seller quality		.077 (.006)**		.027 (.005)**	.023 (.005)**		.100 (.008)**	.097 (.008)**
Product risk		.010 (.005)**		-.002 (.006)	.001 (.006)		.033 (.007)**	.036 (.008)**
Gender		-.003 (.006)		.003 (.007)	.003 (.007)		-.009 (.007)	-.009 (.007)
Age		-.021 (.006)**		-.023 (.006)**	-.023 (.006)**		-.006 (.006)	-.007 (.006)
Membership duration		-.006 (.006)		.001 (.006)	.000 (.006)		-.004 (.007)	-.004 (.007)
Seller popularity		.024 (.006)**		.033 (.007)**	.033 (.007)**		-.006 (.007)	-.006 (.007)
Product popularity		-.033 (.005)**		.025 (.006)**	.025 (.006)**		-.095 (.006)**	-.095 (.006)**
Type of commerce (B2C vs. C2C)		.040 (.005)**		-.016 (.006)**	-.016 (.006)**		.113 (.008)**	.113 (.008)**
Transaction frequency							-.044 (.005)**	-.044 (.005)**
Transaction spending				-.043 (.005)**	-.044 (.005)**			
Time		Yes		Yes	Yes		Yes	Yes
Mill's ratio		Yes		Yes	Yes		Yes	Yes
City		Yes		Yes	Yes		Yes	Yes
Number of observations		24810		24810	24810		24810	24810
R^2		.092		.079	.080		.063	.063
Adjusted R^2		.088		.076	.076		.059	.059
F-value		24.170		20.670	20.420		16.060	15.830
Root MSE		642.620		5.532	5.530		107.550	107.530

* $p < .05$, ** $p < .01$.

Notes: Standard errors are in parentheses. We provide the fitted R-square, using the normal variance estimate, because we relied on the robust variance estimate.

Table 5

STUDY 1: TRANSACTION-LEVEL ANALYSIS RESULTS ON THE EFFECT OF MOBILE TRANSACTION ON DECOMPOSED TRANSACTION SPENDING

Dependent Variable		**Product Price**			**Product Quantity**	
		Model 1	**Model 2**		**Model 3**	**Model 4**
		Main Effect (Linear)	**Main and Interaction (Linear)**		**Main Effect (Linear)**	**Main and Interaction (Linear)**
Main Effects						
Mobile transaction	$\mathbf{H_{4a}}$	-.017 (.002)**	-.014 (.003)**	$\mathbf{H_{4b}}$	-.024 (.002)**	-.022 (.004)**
Moderating Effects						
Mobile transaction × Seller quality	$\mathbf{H_{5a}}$		.006 (.002)*	$\mathbf{H_{5b}}$		.012 (.003)**
Mobile transaction × Product risk	$\mathbf{H_{6a}}$		-.011 (.002)**	$\mathbf{H_{6b}}$		-.017 (.002)**
Control Variables						
Seller quality		.194 (.005)**	.190 (.005)**		.073 (.005)**	.065 (.005)**
Product risk		.086 (.007)**	.092 (.007)**		-.138 (.008)**	-.127 (.008)**
Gender		.068 (.011)**	.061 (.011)**		.130 (.012)**	.119 (.012)**
Age		.006 (.007)	.010 (.007)		-.070 (.008)**	-.063 (.008)**
Membership duration		.018 (.005)**	.016 (.005)**		.040 (.006)**	.035 (.006)**
Seller popularity		.051 (.006)**	.055 (.006)**		-.094 (.007)**	-.088 (.007)**
Product popularity		-.111 (.003)**	-.113 (.003)**		-.075 (.003)**	-.077 (.003)**
Type of commerce (B2C vs. C2C)		.242 (.005)**	.244 (.005)**		-.213 (.005)**	-.209 (.005)**
Prior stage mobile ratio		-.003 (.002)	-.003 (.005)		-.003 (.003)	-.003 (.003)
Product quantity		-.400 (.002)**	-.400 (.002)**			
Product price					-.445 (.003)**	-.446 (.003)**
City		Yes	Yes		Yes	Yes
Time		Yes	Yes		Yes	Yes
Mill's ratio		Yes	Yes		Yes	Yes
Number of observations		218330	218330		218330	218330
R^2		.410	.411		.344	.344
Adjusted R^2		.409	.410		.344	.344
F-value		1244.010	1220.930		618.22	607.87
Root MSE		1.018	1.018		.889	.889

* $p < .05$, ** $p < .01$.

Notes: Standard errors are in parentheses. We used a weighted least square model to analyze the transaction-level data.

Table 6

STUDY 2: FIRM-LEVEL ANALYSIS RESULTS ON THE EFFECT OF FIRM MOBILE TRAFFIC RATIO ON FINANCIAL PERFORMANCE

Dependent Variable		**Financial Performance**	
		Model 1	**Model 2**
		Main Effect (Inverted U-Shaped)	**Main and Interaction (Inverted U-Shaped)**
Main Effects			
Mobile traffic ratio		.235 (.097)*	.536 (.157)**
Mobile traffic ratio^2	$\mathbf{H_7}$	-.313 (.098)**	-.530 (.146)**
Moderating Effects			
Mobile traffic ratio × Operating efficiency			-.610 (.452)
Mobile traffic ratio^2 × Operating efficiency	$\mathbf{H_{8a}}$		.530 (.263)*
Mobile traffic ratio × Website cognitive load			.290 (.169)
Mobile traffic ratio^2 × Website cognitive load	$\mathbf{H_{8b}}$		-.338 (.149)*
Mobile traffic ratio × Online store presence			-.604 (.276)*
Mobile traffic ratio^2 × Online store presence	$\mathbf{H_{8c}}$		.351 (.194)
Control Variables			
Operating efficiency		-.054 (.066)	.088 (.226)
Website cognitive load		-.062 (.050)	-.013 (.057)
Online store presence		-.069 (.033)*	.210 (.120)
Total traffic		-.013 (.023)	-.016 (.023)
Website popularity		.017 (.028)	.025 (.026)
Firm size		-.252 (.078)*	-.202 (.077)**
Firm revenue		.316 (.085)*	.250 (.079)**
Industry competitiveness		.037 (.025)	.029 (.025)
Industry dynamism		-.020 (.040)	-.033 (.040)
Industry growth		-.009 (.028)	-.003 (.027)
Lag financial performance		-.042 (.060)	-.001(.048)
Month		Yes	Yes
Number of observations		1301	1301
R^2		.059	.097
Adjusted R^2		.043	.076
F-value		3.750	4.790
Root MSE		.004	.004

* $p < .05$, ** $p < .01$.

Notes: Standard errors are in parentheses.

Appendix A
STUDY 1 ROBUSTNESS ANALYSIS: LEVEL-IN-LEVEL ANALYSIS OF THE OPTIMAL MOBILE SHOPPING RATIO

Dependent Variable	**Customer Sales (Inverted U-Shaped)**
Main Effects	
Mobile shopping ratio	.127 (.018)**
Mobile shopping ratio^2	-.146 (.019)**
Control Variables	
Seller quality	.067 (.006)**
Product risk	.009 (.007)
Product popularity	-.032 (.003)**
Gender	-.023 (.009)**
Age	.029 (.003)**
Membership duration	-.017 (.004)**
Seller popularity	.044 (.008)**
Type of commerce	.038 (.006)**
Time	Yes
City	Yes
Mill's ratio	Yes
Number of observations	39459
R^2	.057
Adjusted R^2	.054
F-value	97.370
Root MSE	1198.800

* $p < .05$, ** $p < .01$.
Notes: Standard errors are in parentheses. We provide the fitted R-square, using the normal variance estimate, because we used the robust variance estimate.

Appendix B
STUDY 1 ROBUSTNESS ANALYSIS: TRANSACTION-LEVEL ANALYSIS ESTIMATION RESULTS ON THE EFFECT OF MOBILE TRANSACTION ON TRANSACTION SPENDING

Dependent Variable	**Transaction Spending**	
	Model 1	**Model 2**
	Main Effect (Linear)	**Main and Interaction (Linear)**
Main Effects		
Mobile transaction	-.028 (.003)**	-.024 (.004)**
Moderating Effects		
Mobile transaction × Seller quality		.012 (.003)**
Mobile transaction × Product risk		-.021 (.003)**
Control Variables		
Seller quality	.217 (.006)**	.209 (.006)**
Product risk	.006 (.009)	.019 (.009)*
Product popularity	-.138 (.004)**	-.140 (.004)**
Gender	.131 (.014)**	.118 (.014)**
Age	-.034 (.009)**	-.026 (.009)**
Membership duration	.039 (.006)**	.033 (.006)**
Seller popularity	-.003 (.008)**	.004 (.008)
Type of commerce (B2C vs. C2C)	.107 (.006)**	.112 (.006)**
Prior stage mobile ratio	-.003 (.008)	-.004 (.003)
City dummy	Yes	Yes
Time	Yes	Yes
Mill's ratio	Yes	Yes
Number of observations	218330	218330
R^2	.102	.103
Adjusted R^2	.102	.102
F-value	157.770	156.01
Root MSE	1.106	1.105

* $p < .05$, ** $p < .01$.

Notes: Standard errors are in parentheses. A weighted least square model is used to analyze the transaction-level data.