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App Adoption: The Effect on Purchasing of Customers Who Have Used a Mobile Website Previously

Huan Liu [a,b,*] & Lara Lobschat [a] & Peter C. Verhoef [a] & Hong Zhao [b]

[a] University of Groningen, Faculty of Economics and Business, Department of Marketing, Nettelbosje 2, 9747 AE Groningen, the Netherlands
[b] University of Chinese Academy of Sciences, School of Economics and Management, Zhongguancun East Road No.80, 100190 Beijing, China

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Abstract

A key question for retailers who already offer a mobile website is, whether they should add an app as an additional purchase channel. We address this issue by exploring whether consumers' app adoption stimulates additional purchases and how this change in purchase behavior differs across customers with different levels of spending share for different product categories and customer loyalty. By using transactional data from a Chinese online retailer, we show that app adopters have higher purchase incidence, buy more frequently, and spend more in each order than non-adopters. We also find that app adoption has a stronger positive effect on the order size of customers who have a lower spending share of high-price products and customers who are less loyal to the focal retailer. Hereby, we contribute to multichannel and mobile marketing literature by empirically examining the effects of adding a similar (mobile) purchase channel to an already established (mobile) purchase channel. Managerially, our results suggest that apps are worth investing in despite their similarity to mobile websites and can induce non-loyal customers to purchase more and thus potentially foster these customers' loyalty.

Keywords: Mobile channels; App adoption; High-price products; Customer loyalty

Introduction

With the increased and remarkable usage of mobile devices during consumers' purchase journey, consumption in mobile channels is constantly growing (Meola 2016). Case in point is a recent Google study, which revealed that more than 40% of online transactions are already conducted on mobile devices (Lacy 2018). Two notable mobile channels are mobile websites and mobile applications (hereafter: apps). Both of them are designed for the small touch screen of mobile devices. The former is based on the technology of browser-HTML pages which are similar to online websites; an app is a separate system and specifically designed for certain platforms such as Android, iOS, or Windows based on more complicated technologies. Developing and maintaining an app usually requires more investment of time and money compared to a mobile website (Doom 2014). Thus, in practice, most online retailers planning to step into mobile commerce first expand their business to mobile websites. As an example, in China, retailers can easily and freely offer a WeChat shop within five minutes, which is a mobile website that connects to the menu of the retailer's WeChat[1] Official Account (Chen 2017). Further, consumer research indicates that 62% of customers purchase through mobile websites whereas only 38% do so through apps (Panico 2013). However, recently a study revealed that 90% of a consumer's mobile time is spent using apps, indicating that app

* Corresponding author.
E-mail addresses: huan.liu@rug.nl (H. Liu), l.lobschat@rug.nl (L. Lobschat), p.c.verhoef@rug.nl (P.C. Verhoef), zhaohong@ucas.ac.cn (H. Zhao).

[1] WeChat is the most widely used app in China and an equivalent of combination of WhatsApp, Facebook, and PayPal, with 889 million monthly active users (please see https://chinachannel.co/1017-wechat-report-users/).

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usage dominates the usage of mobile websites (Chaffey 2017). Consequentially, a key question for retailers who already offer a mobile website is whether adding an app as another mobile purchase channel serves as an efficient strategy.

In previous multichannel literature, most studies explore the context of adding an app to an existing online website (e.g., Huang, La, and Ba 2016; Kim, Wang, and Malthouse 2015; Wang, Malthouse, and Krishnamurthi 2015). This literature demonstrates that adding an app increases consumers' purchase likelihood. However, the channel difference between apps and online websites is notably larger than the difference between apps and mobile websites. Apps and online websites are approached through different devices with distinct characteristics (e.g., difference in screen size), while both apps and mobile websites can be accessed through mobile devices and have a similar layout. Also, apps and online websites are used in different contexts (e.g., on the go vs. at home), while the usage contexts of apps and mobile websites are more similar. Thus, it is not clear whether adding an app to a mobile website would lead to changes in consumers' purchase behavior as the effect of adding an app to an online website cannot be extended to adding an app to a mobile website. One of the only studies which explores the addition of an app to a mobile website finds that adopting an app significantly spurs additional consumer visits to the mobile website (Xu et al. 2014). However, the authors focus on the publishing industry with consumers visiting a news mobile website (or the respective app) and their subscription decisions instead of retail transactions. The subscription of news in their setting is likely to involve lower financial risks than retail transactions. Besides, consumers might perceive different levels of risk related to apps and mobile websites, which will further influence their purchase behavior in the two channels. Thus, the findings of mobile usage of news cannot be generalized to products with monetary transactions. This is our motivation to explore how consumers' purchase behavior changes after adopting an app besides an existing mobile website.

We first examine whether there is a change in customers' purchase incidence and actual purchases (i.e., purchase frequency and order size) after they adopt an app as a mobile purchase channel. We apply propensity score matching to reduce self-selection issues of customers adopting the app and jointly estimate a model with three equations to test our hypotheses. Neslin et al. (2006) indicate that customers with different characteristics show distinct purchase behavior in specific channels. In our study, we also account for differences between customers and specifically consider how customers' spending share of different product categories and customer loyalty impact the effect of app adoption on purchase behavior.

In addressing the above questions, the current paper contributes to the literature on multi/omni-channel retailing and mobile marketing. Existing multi/omni-channel studies have mainly discussed effects of channel addition for very different channels, for example, adding an online website to physical stores and vice-versa (e.g., Avery et al. 2012; Homberg, Vollmayr, and Hahn 2014; Melis et al. 2016; Pauwels and Neslin 2015; van Nieron et al. 2011), or adding an app to an online website (e.g., Huang, Lu, and Ba 2016; Kim, Wang, and Malthouse 2015; Wang, Malthouse, and Krishnamuurthy 2015). For example, Melis et al. (2016) show that consumers tend to select the online store belonging to the same chain as their preferred offline store.

We contribute to this literature and Xu et al. (2014) by considering the setting of adding an app to a mobile website and by exploring the change of app adopters' real purchase behavior. We clearly show that the app adopters are more likely to purchase, purchase more frequently, and spend more in each order than non-adopters. Second, we discuss how app adopters' increased spending differs across customers. We find that app adopters who have a lower spending share of high-price products purchase more in each order than customers with a higher spending share of this category; on the other hand, app adopters who show higher loyalty to the focal retailer purchase less in each order than non-loyal customers. The two significant moderating factors provide evidence that apps could mitigate customers' perceptions of financial risk and foster loyalty which we will discuss in detail later.

The remainder of this paper proceeds as follows. The next section reviews the current literature. The subsequent section presents specific hypotheses. We then introduce the data set and also our empirical analyses. After that, we discuss our results based on our econometric models. The concluding part proposes implications for academics and practitioners and presents directions for future research.

Literature Review

Shopping through mobile channels changes the way consumers behave (Shankar et al. 2016). First, consumers can purchase at any time, at any place even when they are on the go, and do not necessarily have to travel to physical stores or sit in front of a computer (e.g., Lee, Kim, and Kim 2005; Verhoef, Kannan, and Inman 2015). Second, consumers can easily and jointly use mobile devices with other channels, for instance, by searching for information, by checking stocks or by comparing prices on their mobile phone when they are in an offline store (e.g., Melero, Sese, and Verhoef 2016). Third, consumers can have real-time interactions with friends, retailers, and other consumers via mobile devices when purchasing (e.g., Shankar et al. 2016; Verhoef, Kannan, and Inman 2015). With the appearance of these changes, mobile channels have become increasingly important both for retailers and consumers.

Most research explores why customers adopt mobile technologies and channels by using the technology acceptance model and its extended versions (e.g., Bruner and Kumar 2005; Hubert et al. 2017; Ko, Kim, and Lee 2009; Zhou, Lu, and Wang 2010). These studies are mainly based on customer perceptions derived from technologies (e.g., usefulness, ease of use, enjoyment) and customers' psychological heterogeneity (e.g., visual orientation, innovation, task-technology fit). Our paper will not address antecedents of mobile adoption, which is why we will not discuss these studies in detail. Nevertheless, previous research derives benefits (and/or costs) of mobile channels from comparing them with online channels (either in an explicit or inexplicit way). These studies present slightly different views on the distinct features of mobile channels (Huang, Lu, and Ba 2016), which can be summarized as mobility (or portability), ubiquity, personalization, identity, and localization (Clarke 2001; Lee 2005; Shankar and Balasubramanian 2009; Wu et al. 2011). Only a few studies investigate the differences within mobile channels, i.e., mobile websites and apps. These studies argue that mobile websites are easy to use because they do not need to be downloaded, installed, and/or updated (Mikkonen and Taivalsaari 2011; Xu et al. 2014); while apps have more interactive user interfaces (Xu et al. 2014) and can take advantage of device features more comprehensively, such as location services and the integrated camera (Alang 2010; Mikkonen and Taivalsaari 2011).

Recent studies on multi-channel management have paid much attention to the influence of adding online channels to offline channels on customers' purchase behavior. One consistent conclusion is that with the increase of the number of channels consumers use in their purchase journey, their spending increases (e.g., Kushwaha and Shankar 2013; Melis et al. 2016; Montaguti, Neslin, and Valentini 2015). This is because multiple channels provide customers with more flexible choices and improve perceived convenience (Ansari, Mela, and Neslin 2008). The availability of new channels and the information provided enables consumers to gain more knowledge about retailers and enhances their awareness and positive associations with retailers (Keller 2010).

This is also supported for the addition of apps to a multichannel mix. The relative advantages of apps attract additional purchases. For example, studies find that app adopters have higher purchase frequency and a higher spending level than non-adopters (Huang, Lu, and Ba 2016; Narang and Shankar 2016; Wang et al. 2015). Other studies provide evidence for different cross-channel effects of adding apps. For example, research by Dinner, van Heerde, and Neslin (2015) finds that accessing an app improves customers' purchase incidence both in offline and online channels. However, the authors treat a retailer's app and online website jointly as online channels and do not differentiate between consumers' purchase behavior in these two channels. Huang, Lu, and Ba (2016) reveal that an app slightly cannibalizes purchases in an existing online website. Huang et al.'s finding can be explained by attribute differences across channels. Studies indicate that synergy effects tend to happen when channels have complementary attributes, which exist, for example, between online and offline channels (Deleersnyder et al. 2002; Dholakia, Zhao, and Dholakia 2005). On the other hand, cannibalization effects tend to appear when channels have similar attributes. For instance, physical stores are more likely to cannibalize catalogs than online websites regarding consumers' purchase likelihood, since stores and catalogs share more common attributes than online websites, such as fostering experiential shopping, having similar customer segments, and requiring similar human capital (Avery et al. 2012; Pauwels and Neslin 2015). Despite the evidence that cannibalization exists at the channel level, when looking specifically at mobile apps, research suggests that a customer who adopts an app shows higher purchase likelihood and also higher actual spending in total (e.g., Dinner, van Heerde, and Neslin 2015; Huang, Lu, and Ba 2016; Wang, Malthouse, and Krishnamurthi 2015). Table 1 summarizes related papers on the effect of app adoption and presents how our study adds to existing research.

Hypotheses Development

Main Effects of App Adoption

Existing studies provide evidence that app adoption creates benefits for customers who use online channels for purchasing (e.g., Kim, Wang, and Malthouse 2015; Narang and Shankar 2016). We argue that these benefits are also supported for app adopters who have purchased through mobile websites previously, but in a different way. Consumers can access any mobile website on their phones but cannot or will not access too many apps due to the limitation of phone capacity and the cognitive effort of finding a specific app from a messy app arrangement. However, apps are more flexible and more convenient across various contexts than mobile websites. Consumers can access both mobile websites and apps to search information and purchase products in situations with network coverage, but they can only use apps (although some functions are limited) in situations without network connection because mobile websites only work if the Internet is available (Gazdecki 2016). Thus, the most significant feature of mobile channels—ubiquity, is more strongly supported for apps than mobile websites. Apps' superior availability allows users to engage in mobile activities without any limitations of time and locations (e.g., Rapp et al. 2015). Consumers could further perceive greater convenience and user control derived from apps' ubiquity, which strongly and positively influence usage intention and participation (Kleijnen, De Ruyter, and Wetzels 2007; Wang, Krishnamurthy, and Malthouse 2018). Besides, apps also create higher perceived control in multi-tasking situations. For example, it is much easier for consumers to switch across different apps than to switch from one mobile website to another. Research shows that greater perceived control is conducive to customers' positive feelings (Ittelson et al. 1974) and reduces their uncertainty surrounding purchase decisions (Ariely 2000), thus improving their confidence and perceived value of a specific choice (e.g., Hourahine and Howard 2004; Kleijnen, De Ruyter, and Wetzels 2007). Moreover, perceived value is a key element influencing buying choices and higher perceived value leads to higher willingness to buy (e.g., Chang and Wildt 1994).

The second prominent advantage of apps relative to mobile websites is their (potential) ability to generate pleasant experiences and to lock-in customers (e.g., Dinner, van Heerde, and Neslin 2015). Apps have a more user-friendly interface with more interactive features, load information faster, and integrate device-features more comprehensively;

Table 1
Most related literature on the effect of app adoption on customer purchase.

Reference	Research setting	Dependent variable(s)	Moderator(s)	Analyzing level	Relevant findings
Wang et al. 2015	Adding an app to an existing online website	Purchase frequency Oder size	Customer spending prior to adopting the app	Individual level	Customers' purchase frequency and low-spending customers' order size increase after adopting the app. App adopters tend to buy habitual products in mobile channels.
Kim et al. 2015	Only consider app usage	The number of shopping apps a customer possess The number of shopping apps used for purchases	–	Individual level	Digital experience and browsing information from shopping apps can explain customers' purchase decisions in apps.
Narang and Shankar 2016	Adding an app (no in-app purchases) to an existing online website	Incidence and monetary value for purchase and return	–	Individual level	App adopters buy 21% more often but spend 12% less per occasion and return 73% more often than non-adopters in the month after adoption. Overall, app adoption leads to a 24% increase in net monetary value of purchases.
Dinner et al. 2015	Adding an app to an online website and physical stores	Mobile app access Purchase incidence	–	Individual level	Consumer purchase incidence is significantly driven by app usage; this relationship is stronger for consumers' online purchase than offline purchase.
Wang et al. 2018	Adding an informational app in a coalition loyalty program	Points accrued Points used for reward redemption	Customer segments	Individual level	App adoption increases customers' accruals. The app adoption has greater effect on occasional customers' accruals than active and accruing customers, and has greater impact on active customers' redemptions than occasional customers.
Huang et al. 2016	Adding an app to an existing online website	Purchase frequency Oder size Total spending	–	Individual and channel level	After adopting the app, customers' purchases on the online website were slightly cannibalized; however, the consumers' purchases increased overall. The consumers' order size decreases after adopting the app.
Xu et al. 2014	Adding a news app to an existing (news) mobile website	Visit likelihood	User diversity of news consumption Consumers' temporal budget	Individual level	The adoption of a news app leads to a significant increase in visiting incidence on the mobile website. This effect is higher for consumers with high valuation for concentrated news contents and with less time-constraint.
Our paper	Adding an purchasing app to an existing mobile website	Purchase incidence Purchase frequency Order size	Spending share of high-price products Spending share of credence products Customer loyalty	Individual level, with an additional channel level	Customers' purchase incidence, purchase frequency, and order size significantly increase after adopting the app. The positive effect of app adoption on order size is stronger for less loyal customers and customers with lower spending share of high-price products.

on the other hand, mobile websites normally make use of navigational interfaces which are organized as hierarchical hypertext and hypermedia (e.g., Alang 2010; Summerfield 2017; Xu et al. 2014). Such relative advantages of apps make it easier for consumers to interact with retailers (e.g., Bellman et al. 2011), which further increases consumers' perception of ease of use, shopping enjoyment, and willingness to continue the relationship with retailers (e.g., Coursaris and Sung 2012; Kim et al. 2013). For instance, a survey reports that customers who purchase through apps are significantly more satisfied with their experience than customers purchasing on mobile websites (Panico 2013). In addition, apps keep customers loyal to brands by allowing them to access benefits such as offers and promotions with their personal accounts automatically (Slavick 2017). Also, apps tend to have better customer data management systems than mobile websites. Apps request customers to fill in personal information (e.g., name, phone number, email) when logging in, which only needs to be done once since apps save customer information after the first registration. With subsequent usage, apps automatically enter into one's own account and track search and purchase histories. Mobile websites, on the other hand, normally do not save login information and need consumers to fill in the information every time they log on or purchase, which requires more cognitive efforts. Therefore, apps allow easier management of consumers' personal accounts, such as checking membership and loyalty points, adding products to their favorite lists, and tracking parcels on the go. This advanced account management improves the relationship between customers and retailers (Hourahine and Howard 2004). In general, these features of apps enable customers to engage more with retailers and therefore are more likely to lock-in customers.

Third, we argue that apps are perceived as less risky for purchasing than mobile websites. A retailer's mobile website can be accessed from other web links which include and recommend the focal mobile website. In case of information leakage and financial loss during payment, users do not know who is responsible for the failure: the initial website or the focal website, in which case users are very sensitive to such risks (Bahli and Benslimane 2004). Besides, mobile websites request customers' contact information for every login, and also request customers' payment information for every purchase without logging in. Mobile websites thereby easily put consumers in an open and insecure situation, further increasing the possibility of a data breach. Relatively speaking, an app presents a closed environment because it can neither be accessed through external web links nor repeatedly requests personal and payment information. Also, before installing an app, its background process warns and requests users' permission for access to specific resources (e.g., Peng et al. 2012), such as personal contact information and locations. Privacy statements of apps normally clarify how retailers will protect customer information and which parties will have permissions to the data, and how they will use it. By doing this, the risk of installing is communicated to users and also a commitment is made for protecting customer privacy. Mobile websites do not provide or at least do not remind customers of such privacy agreements. Accordingly, the additional presence of the requirement and reminder of personal information enhances users' trust of selected apps (Chin et al. 2012). Taken together, from the perspective of usage scenarios, we can infer that consumers will perceive a lower level of risk when purchasing through apps than through mobile websites. To further support this argument, we approached 459 university students and company employees in China with a simple survey with the aim to investigate consumers' risk perception of purchasing in apps and mobile websites. The survey (see Appendix A) indeed reveals that more than 57% of participants perceive apps as less risky than mobile websites for purchasing; only 2.83% of customers perceive it the other way around; about 21.13% of people think the risk level in apps and mobile websites is similar.

In sum, we have discussed flexibility and convenience, better experience and locking in customers as well as less risk as apps' main advantages relative to mobile websites. We also summarize the above comparisons between apps and mobile websites in Table 2. These channel attributes are important factors influencing customers' purchase decisions. Multiple studies provide evidence supporting that such advantages of apps encourage customers to engage more with retailers and positively affect their value perception of purchasing in an app, thus increasing their interest, positive attitude, and purchase intention for a focal brand or retailer (e.g., Bellman et al. 2011;

Table 2
Differences between mobile apps and mobile websites.

Dimensions	Mobile apps	Mobile websites
Flexibility and convenience	• The number of apps customers access on their phones is limited by phone capacity and the cognitive effort of finding a specific app from many apps • Can be accessed with or without network connection • Are more flexible in multi-tasking situations	• The number of mobile websites visited is not limited. • Can be accessed only with network connection
Customer experience	• Have more user-friendly interface, load information faster, and integrate device-features comprehensively • Can save customer information and allow customers to manage personal accounts easily	• Have navigational interfaces • Do not save login information and need consumers to fill in the information every time when they log on
Perceived risk	• Present a closed environment • Provide and reminder customers of privacy statements	• Can be accessed from external web links

Kleijnen, De Ruyter and Wetzels 2007; Nysveen, Pedersen, and Thorbjornsen 2005).

Prior research has also considered behavioral effects of app adoption. (e.g., Huang et al. 2016; Kim et al. 2015; Narang and Shankar 2016; Wang et al. 2015). Studies by Narang and Shankar (2016) and Kim et al. (2015) reveal that customers' spending increases after adopting the app. However, it is not clear whether such an increase is caused by an increase in purchase frequency, in average order size, or both. Huang et al. (2016) and Wang et al. (2015) model app adopters' purchase frequency and order size. The two studies reveal an increase in purchase frequency for customers after adopting an app than that before the adoption, but obtain inconsistent results for order size. Huang et al. (2016) find customers' order size decreases after app adoption, while Wang et al. (2015) shows a positive effect of app adoption but only for low-spending customers. Huang et al. (2016) argue that mobile channels are better for buying inexpensive products and appropriate for baskets with smaller quantity due to the smaller screen compared to online websites. Thus, customers will have lower order size after adopting an app; the authors do find significant negative effect of app adoption on order size. However, this is not the case in our setting since both apps and mobile websites are accessed through small-screen devices. Wang et al. (2015) do not find a significant effect of app adoption on order size in general. However, after separating samples as low- and high-spending customers, the authors show a positive effect on low-spending customers' order size. The attractiveness of apps over online websites induce these customers to purchase more; while high-spending customers have saturated purchase needs and thus show a limited space for spending growth in each basket after adopting an app. Nevertheless, based on our argument of superior advantages of apps (vs. mobile websites), we expect a strong positive impact of app adoption on customers' subsequent purchasing. Hence, we hypothesize:

H_1. *After adopting an app, customers' (a) purchase incidence, (b) purchase frequency, and (c) order size increase.*

Moderating Effects of Customer Characteristics

Based on our assumption in the above main effect, we propose that less risk is a strong advantage of apps over mobile websites, thus we also account for diverging effects of app adoption by involving customer behavioral characteristics related to risks. We first employ price as a proxy of financial risks and credence (vs. non-credence) attribute as a proxy for the performance risk of products. We then adopt the spending share of high-price and credence products to describe the major risks consumers have taken in their purchasing history. Second, we also consider customer loyalty to the focal retailer prior to launching the app as a potential moderator which influences app adopters' spending, since non-loyal and loyal customers have different perceptions of risk of a focal retailer and thus might show distinct purchasing behavior after adopting an app.

Moderating Effect of Price and Product Category

Jacoby and Kaplan (1972) identify and decompose perceived risks into five facets, i.e., performance, financial, physical, social, and psychological risks. Sweeney, Soutar, and Johnson (1999) indicate that financial and performance risks have critical influence on customers' perceived value in a retail environment. Other studies further show that financial and performance risks are the major risks associated with online purchasing (e.g., Bhatnagar, Misra, and Rao 2000; Bhatnagar and Ghose 2004). Therefore, we also try to identify which role financial and performance risks play in mobile purchasing.

Research finds that price is positively related to perceived financial risk (White and Truly 1989) and in fact is an inherent component of perceived financial risk (Grewal, Gotlieb, and Marmorstein 1994). Thus, we extract the price of products as a proxy of financial risk (De Haan et al. 2018). Second, we involve spending share of credence products as a proxy of performance risk. The reason of doing so is that credence products are those whose quality is highly difficult to be assessed before and even after consumption (Darby and Karni 1973; Nelson 1970; Nelson 1974). Consumers face the highest performance risk when purchasing credence products relative to other products (e.g., Girard and Dion 2010; Mitra, Reiss, and Capella 1999).

As mentioned in the discussion about our main effects, we assume apps to be less risky than mobile websites. A higher spending share of high-price or credence products in the pre-period suggests that customers are accustomed to purchasing products with high risks on the existing mobile website. In such cases, the attribute of apps' lower risk does not lead to much benefit for these customers. In contrast, customers with lower spending share of high-price or credence products might be more concerned about security issues on the mobile website, and only be willing to take a lower level of risk in a given situation. These customers tend to be risk averse. Studies imply that risk-averse consumers prefer low-risk choices and try to reduce the risk of a specific decision (e.g., Gemünden 1985). Therefore, these customers will gain more benefit than others when purchasing in apps since apps mitigate their perceived risk. Apps could lead risk-averse consumers to perceive less uncertainty and be more assured to buy, which improves the possibility of purchasing for these customers. Further, risk-averse customers would engage more with retailers and show more positive feelings and higher value perceptions due to apps' less risk. In this vein, app adopters who have lower spending share of high-price or credence products will spend more than customers with high spending share of such categories. To be consistent with our main hypotheses, we expect that apps' benefits for different customers could influence purchase incidence and actual purchases; the change in actual purchases can be captured by the change in purchase frequency and order size. Thus, we propose:

H_2. *The positive effect of app adoption on (a) purchase incidence, (b) purchase frequency, and (c) order size is weaker* *for customers who have higher spending share of high-price products.*

H$_3$. *The positive effect of app adoption on (a) purchase incidence, (b) purchase frequency, and (c) order size is weaker for customers who have higher spending share of credence products.*

Moderating Effect of Customer Loyalty

Loyal customers tend to have greater trust in retailers and have more personal purchase experience at focal retailers (e.g., Ball et al. 2004; Gefen 2002), thus perceiving lower purchasing risk when buying (Mitchell and Greatorex 1993). Non-loyal customers have less experience of purchasing at a focal retailer and therefore perceive higher uncertainty due to being unfamiliar with the retailer. The app helps reduce non-loyal customers' perceived risk during purchases. Also, non-loyal customers will gain more from apps' advantages than loyal customers due to a ceiling effect associated with diminishing sensitivity, which means that the sensitivity to changes on a specific dimension reduces when the magnitude of the dimension increases (Torgerson 1958). In our case, apps have capabilities to lock-in customers due to their flexibility, convenience and ease of interaction etc. In the vein of diminishing sensitivity, these capabilities would be more influential on non-loyal customers, indicating that apps can offer higher marginal benefit for customers who have lower loyalty than for loyal customers. The greater attraction of apps to non-loyal customers could be reflected in their higher spending. Again, we expect non-loyal adopters not only to show higher possibility of purchasing but also have more actual purchases than loyal customers. Therefore, we propose:

H$_4$. *The positive effect of app adoption on (a) purchase incidence, (b) purchase frequency, and (c) order size is weaker for loyal customers than non-loyal customers.*

Empirical Analyses

Data Collection

We obtained a unique dataset from a Chinese retailer selling non-prescription drugs and cosmetics. Consumers can purchase through multiple channels: physical stores, an online website, a mobile website available from February 1, 2016, and an app released on October 1, 2016. For this retailer, physical stores are mainly responsible for distribution and after-sales services. Digital (i.e., online and mobile websites as well as the app) is major sales channels for the retailer. There is no difference between the product assortment and prices across channels.

Our dataset covers the period from February 1, 2016 to September 30, 2017. Given our research goals and the retailer's company policies, the retailer only provided us with customer transactional data from the app and the mobile website. Initially, we obtained information of 3,378 unique customers with 13,654 orders. The transactional data include the customer ID, the customer zip code, basket information, and the channels used for each order. To test the effects of app adoption on consumers' purchase behavior, we split our data period into two parts: a pre-period from February 1, 2016 to October 1, 2016, and a post-period after the availability of the app on October 1, 2016 to September 30, 2017.

We define app adopters as customers who used the app at least once in the post-period. To control for the potential endogeneity of entering or exiting the retailer, we subset a sample of customers who make at least one order in both pre- and post-periods (Gill et al. 2017). We obtained 605 customers in this step, of which 465 customers are app adopters and 145 customers are non-adopters. By doing this, we can also calculate pre-period purchase behavioral variables for all customers to estimate their likelihood to adopt the app in the next steps. Fig. 1 shows the average spending, purchase

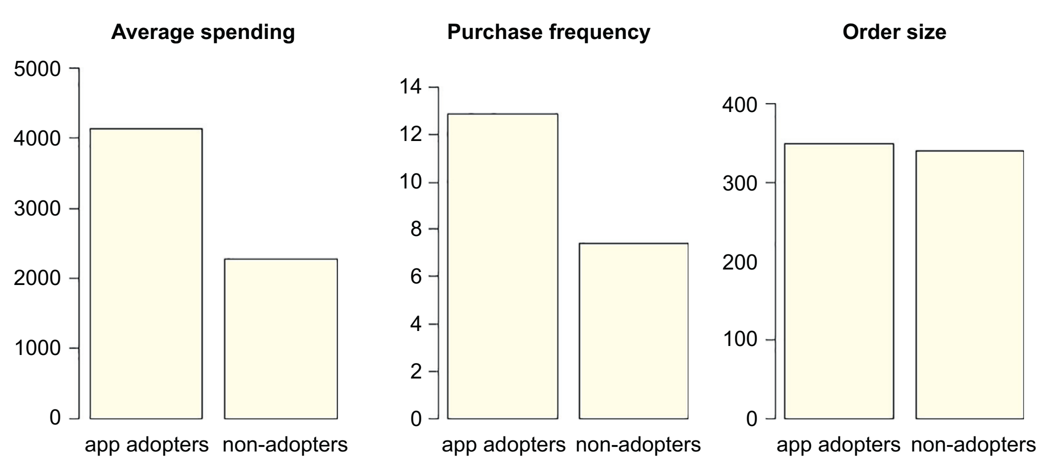

Fig. 1. Average spending, frequency, order size of adopters versus non-adopters. Note:465 adopters and 145 non-adopters. Average spending and order size are in the unit of Chinese yuan (CNY).

frequency, and order size of app adopters and non-adopters in the post-period. Model-free evidence based on t tests shows that app adopters' spending ($p = .00$) and purchase frequency ($p = .00$) is much higher relative to non-adopters', but their order size is not significantly different from non-adopters' ($p = .53$). This indicates that we need formal analyses to explore the effect of app adoption and also should consider other variables which might influence app adoption's effect.

Operationalization of Variables

We detail the operationalization of our variables in Table 3. Additionally, we explain the operationalization of the three moderators. First, in line with Krishnamurthi and Raj (1991), we adopt customers' purchase orders before the launch of the app as an indicator of customers' behavioral loyalty. Customers with a larger number of orders purchase more often and hence show stronger loyalty to the focal retailer. Second, we classify high- versus low-price products based on a median split of price. Third, our data has the unique advantage of allowing us to classify product as credence or non-credence products, i.e., search and experience products. Search products are those whose attributes can be identified before purchase; experience products are those whose attributes can only be identified after purchase (Darby and Karni 1973; Nelson 1970; Nelson 1974). Credence products are normally found in professional contexts such as medical services and pension plans, i.e., in areas where people predominately do not have expertise to verify their quality and performance (Asch 2001). The non-prescription health care products (e.g., vitamins and anti-aging pills) in our sample are a typical example of credence products; while cosmetics (e.g., essential oil and creams) can be categorized as experience products because they require a real product experience to be able to assess their attributes, for example, whether they are suitable for one's skin. Our data set also contains a few search products, such as toothbrushes and cosmetic bags. Given that search products only represent a small part of the focal retailer's sales, we only differentiate between credence and non-credence products; we classify non-prescription health care products as credence products and classify cosmetics and others as non-credence products. The spending share of credence products for a customer equals the ratio of one's spending on credence products to his/her total spending in the pre-period. The spending share of high-price products is calculated similarly.

Self-Selecting Issue

We first solve a prevailing self-selection issue. Given that customers are not randomly assigned to adopters and non-adopters, those who adopt the app probably are inherently different from non-adopters (e.g., Wang et al. 2015). For instance, app adopters may purchase more before adopting the app, could be younger, and maybe more likely to try new technologies than non-adopters, which leads to selection bias in our analyses. To reduce the self-selecting bias, we applied propensity score matching. Propensity score matching (hereafter: PSM) is a popular matching technique attempting to make

Table 3
Operationalization of variables.

Variable	Variables used in which eq. (P = PSM, I = incidence, F = purchase frequency, S = order size)	Computed during	Description
Independent variables			
ln(Tenure+1)	P, I, F, S	Pre-period	Days between first order to Oct.1 2016
ln(Recency+1)	P, I, S	Pre-period	Days between the last order to Oct.1 2016
ln(Number of orders+1)	P, I, F, S	Pre-period	The number of orders
ln(Spending+1)	P	Pre-period	Total spending
ln(Customer density + 1)	P	Pre-period	The number of customers in each zip code
ln(Average order size +1)	I, F, S	Pre-period	The average order size in the pre-period
SS.highprice	I, F, S	Pre-period	The spending share of high-price products
SS.credence	I, F, S	Pre-period	The spending share of credence products
Propensity score	P, I, F, S	Pre-period	Estimated possibility of being an app adopter based on PSM
Adp	P, I, F, S	Post-period	=1 if a customer is an app adopter; 0 otherwise
$PI_{i,t-1}$	I	Post-period	=1 if a customer purchased in the past month; 0 otherwise
Dependent variables			
P_{it}	I	Post-period	=1 if a customer made a purchase in a given month; 0 otherwise
F_{it}	F	Post-period	Purchase frequency of customer i in a given month t
S_{it}	S	Post-period	Order size of customer i in a given month t

the control and the treatment samples comparable by considering covariates which predict the possibility of being in the treatment group for all observations (Rosenbaum and Rubin 1983; Rosenbaum and Rubin 1985; Rubin 2007).

We used a logit model (the results are shown in Appendix B) to calculate propensity scores for each customer. The propensity score indicates the possibility of being assigned to the treatment group, i.e., app adopters. In the logit model of PSM, observed covariates which might capture the difference between adopters and non-adopters should be integrated. To achieve this goal, studies normally consider customer characteristics as many as they can; the most commonly used characteristics are demographic (e.g., age, gender, education) and behavioral factors (e.g., tenure, spending, order size) (e.g., Huang et al. 2016; Kim et al. 2015; Wang et al. 2015). However, we do not have much customer information except the zip code. Thus, we only include tenure, recency, the number of orders, spending in the pre-period, and also customer density in each zip code as covariates in the logit model. To improve the predictive performance, we also included several interactions of the covariates (e.g., Steiner and Cook 2013; Stuart 2010). We then matched the treatment and control group by using the propensity scores generated from the logit model. We employed the nearest neighboring matching method with replacement due to lack of samples in the control group. The PSM procedure identified 584 matched customers, i.e., 450 adopters and 134 non-adopters.

We then checked whether assumptions of the PSM are met and whether the PSM performed well. First, we confirmed the region of common support condition through visual analyses (see Appendix B) and it shows that a partial overlap exists between the control and treatment group. Also, the consistency of propensity distribution between the two groups significantly improved after matching. We then examined covariate balance in the matched sample. All differences in means of covariates and their interactions reduced after matching, indicating the balance between the treatment and control group improved. We further calculated the absolute standard bias of each covariate. All standard biases are smaller than 0.05, which implies that the current matching performed well in balancing the distributions of the covariates (Caliendo and Kopeinig 2008). We report the performance of the PSM in Table 4.

Econometric Model

We organized the dataset with matched customers as a balanced monthly panel data from October 2016 to September 2017. If purchases were observed in a given month, purchase frequency and order size in that month were calculated. Based on Konuş, Neslin, and Verhoef (2014), we adopted a probit model to estimate whether a customer purchases in a specific month or not. In this model, we also included an indicator variable $PI_{i,t-1}$ to capture state dependence, which is defined as whether a customer made a purchase in the previous month (e.g., Dinner et al. 2015; Konuş et al. 2014). We then used two panel regressions to estimate purchase frequency and order size conditional on observing a purchase in a given month. We included individual random effects in the three equations and allowed both random effects and errors to be correlated across equations. We also controlled for past purchase behavior by including average order size and control for the potential selection bias by including the propensity scores. We estimated the three equations simultaneously whereby the purchase frequency and the order size equations were estimated conditional on observing a purchase. In total, we observe 584 customers over the 12-months treatment period, which results in a total of 7,008 records. We present all three equations as follows:

$$\mathrm{P_{it}} = \text{Purchase if } \mathrm{P}^*_{\mathrm{it}}>0; \text{No purchase if } \mathrm{P}^*_{\mathrm{it}} \leq 0$$

$$\mathrm{P}^*_{\mathrm{it}} = \beta_1 \mathrm{X1_{it}} + \xi_{1i} + \varepsilon_{1it} \tag{1}$$

$$\mathrm{F_{it}} = \mathrm{F}^*_{\mathrm{it}} \text{ if } \mathrm{P}^*_{\mathrm{it}}>0; \text{Unobserved if } \mathrm{P}^*_{\mathrm{it}} \leq 0$$

$$\mathrm{F}^*_{\mathrm{it}} = \beta_2 \mathrm{X2_{it}} + \xi_{2i} + \varepsilon_{2it} \tag{2}$$

$$\mathrm{S_{it}} = \mathrm{S}^*_{\mathrm{it}} \text{ if } \mathrm{P}^*_{\mathrm{it}}>0; \text{Unobserved if } \mathrm{P}^*_{\mathrm{it}} \leq 0$$

$$\mathrm{S}^*_{\mathrm{it}} = \beta_3 \mathrm{X3_{it}} + \xi_{3i} + \varepsilon_{3it} \tag{3}$$

Table 4
Summary statistics and covariate comparison before and after matching.

Covariates: Pre-period behavioral characteristics	Treatment group: Adopters (1)	Control group: Non-adopters		Difference-in-mean		Standardized bias	
		Before matching (2)	After matching (3)	Before matching (1)–(2)	After matching (1)–(3)	Before matching	After matching
1 ln(Tenure+1)	4.536	4.511	4.556	0.024	−0.021	0.026	0.023
2 ln(Recency+1)	3.428	3.725	3.464	−0.296	−0.036	0.231	0.028
3 ln(Number of orders+1)	1.565	1.465	1.563	0.099	0.001	0.126	0.001
4 ln(Spending+1)	7.096	6.959	7.126	0.137	−0.030	0.117	0.026
5 ln(Customer density + 1)	3.328	3.387	3.305	−0.059	0.023	0.051	0.020
Interaction 1*4	32.534	31.705	32.838	0.829	−0.304	0.088	0.032
Interaction 3*4	11.852	10.778	11.891	1.074	−0.039	0.142	0.005
Interaction 1*5	15.100	15.202	14.989	−0.102	0.111	0.017	0.018

Table 5
Estimation of three equations: purchase incidence, purchase frequency, and order size.

	Purchase Incidence Equation					
	Main Effects			Interaction with *Adp*		
	Coef.	p-value	Sig.	Coef.	p-value	Sig.
Constant	−2.185	0.00	−			
Adp	0.406	0.00	+			
$PI_{i,t-1}$	0.588	0.00	+			
ln(Tenure+1)	−0.071	0.07	−			
ln(Recency+1)	0.035	0.29	NS			
ln(Average order size +1)	0.035	0.34	NS			
Propensity score	1.244	0.01	+			
ln(Number of orders+1) [a]	0.152	0.02	+	0.057	0.38	NS
SS.highprice	0.082	0.06	NS	−0.192	0.29	NS
SS.credence	0.015	0.92	NS	0.167	0.30	NS
	Purchase Frequency Equation					
	Main Effects			Interaction with *Adp*		
	Coef.	p-value	Sig.	Coef.	p-value	Sig.
Constant	0.620	0.03	+			
Adp	0.147	0.00	+			
ln(Tenure+1)	−0.045	0.02	−			
ln(Average order size +1)	−0.040	0.16	NS			
Propensity score	0.403	0.10	+			
ln(Number of orders+1)	0.085	0.11	NS	−0.033	0.54	NS
SS.highprice	−0.075	0.63	NS	0.106	0.51	NS
SS.credence	−0.013	0.92	NS	0.149	0.27	NS
	Order Size Equation					
	Main Effects			Interaction with *Adp*		
	Coef.	p-value	Sig.	Coef.	p-value	Sig.
Constant	3.151	0.00	+			
Adp	0.221	0.00	+			
ln(Tenure+1)	0.009	0.86	NS			
ln(Recency+1)	0.015	0.71	NS			
ln(Average order size +1)	0.243	0.00	+			
Propensity score	0.113	0.18	NS			
ln(Number of orders+1)	0.166	0.05	+	−0.215	0.01	−
SS.highprice	0.586	0.01	+	−0.529	0.03	−
SS.credence	0.075	0.69	NS	0.055	0.79	NS
	Random Effects			Idiosyncratic Error		
	Variances	p-value		Variances	p-value	
Incidence model	0.043	p < .01		1	−	
Frequency model	0.013	p < 0.01		0.304	p < .01	
Order size model	0.130	p < .01		0.437	p < .01	
	Correlations	p-value		Correlations	p-value	
Incidence/frequency	0.955	p < .01		−0.306	NS	
Incidence/order size	0.088	NS		−0.064	NS	
Frequency/order size	0.001	NS		0.039	NS	

[a] To solve multi-collinearity issues resulting from the interaction between *Adp* and three moderators, we mean-centered the three moderators, i.e., *Number of orders*, *SS.highprice*, and *SS.credence* in the three equations.

P^*_{it} is the latent purchase utility driving customer i to purchase in month t; F^*_{it} and S^*_{it} are similar specifications for purchase frequency and order size. P_{it} equals 1 if customer i made a purchase in month t, 0 otherwise. $X1_{it}$, $X2_{it}$, and $X3_{it}$ are vectors that influence purchase incidence, purchase frequency, and order size, respectively. The ξ is the individual random effect and ε is the error term. The equation estimation was conducted by using CMP in STATA (Roodman 2011).

Results and Robustness Checks

Results

Table 5 shows the results of the jointly estimated model of purchase incidence, purchase frequency, and order size. We find a significant positive effect of app adoption on the three dependent variables ($\beta = 0.406$, 0.147, 0.221 respectively, $p < .01$). These findings indicate that app adopters have higher

Table 6
Estimating results of customers' purchases on the mobile website based on a DID method.

Dependent Variable	Purchase Frequency		Order Size	
	Coef.	p-value	Coef.	p-value
Constant	−2.730	0.00	−14.014	0.00
Adp	0.030	0.63	0.113	0.73
Time	−0.723	0.00	−3.655	0.00
Adp*Time	−0.959	0.00	−5.202	0.00
ln(Average order size +1)	0.085	0.02	0.727	0.00
ln(Tenure+1)	0.089	0.03	0.867	0.00
Propensity score	0.648	0.22	1.197	0.66
ln(Number of orders+1)	0.574	0.00	2.297	0.00

Note: Monthly balanced panel data with 548 matched customers in the mobile website. To simplify estimating, we interpreted records without any purchases as left censored observations and thus adopted Tobit models to separately estimate the above two equations. The data set is from February 2016 to September 2017. The variable Time is a dummy indicator separating the pre- and post-period, i.e., *Time* = 0 means the pre-period from February 2016 to September 2016, *Time* = 1 represents the post-period from October 2016 to September 2017. The treatment effect of app adoption is captured by the interaction of *Adp* and *Time*.

likelihood of purchasing, purchase more frequently, and also spend more in each order than non-adopters, which fully supports H_{1a}, H_{1b}, and H_{1c}. In the equation of order size, two of three moderators have significant negative effects. Specifically, the spending share of high-price products has a significant negative interaction effect with app adoption ($\beta = -0.529$, $p < .05$), suggesting that adopters who spend more on products with high financial risk purchase less in each order than customers spending more on low-risk products. This result supports H_{2c}. The spending share of high-price products does not show any significant interactions with app adoption on purchase incidence and frequency; H_{2a} and H_{2b} are not supported by our results. The spending share of credence products has no significant moderating effect on the three dependent variables, implying that customers who spend differently on products with high performance risk before releasing the app do not show differences in their purchase behavior after adopting the app. Thus, H_{3a}, H_{3b}, and H_{3c} are not supported. Besides, we find a negative interaction effect between the number of orders and app adoption in the order size equation ($\beta = -0.215$, $p = .01$), which is consistent with H_{4c}. The effect of app adoption on order size is stronger for less loyal customers than for highly loyal customers. This partially supports H_4, as we do not find significant interactions for purchase incidence (H_{4a}) and frequency (H_{4b}).

Moreover, despite accounting for spending differences between app adopters and non-adopters in this paper, we do not formally test cross-channel effects in our main model. We, however, conduct an additional analysis of customers' purchases on the mobile website before and after launching the app by using a Difference-In-Differences (DID) method. The result is shown in Table 6, clearly revealing that both app adopters' purchase frequency ($\beta = -0.723$, $p < .01$) and order size ($\beta = -5.202$, $p < .01$) on the mobile website significantly decrease after adopting the app. This provides evidence for a cannibalization effect between the two similar channels, which is in line with Avery et al. (2012). Combining our main results with this analysis, we can infer that customers reduce their spending on the mobile website after adopting the app and allocate more spending to the app.

Robustness Checks

We adopt two approaches to test the robustness of our model specification and another approach to test the robustness with respect to our samples and the self-selecting issue. We present results both from Table 5 and from three robustness checks in Table C1 of Appendix C to compare. The first column of Table C1 is copied from Table 5. In the first robustness check, we still involve random effects in all three equations but estimate them separately. The results are similar to our main models. In the second robustness check, we drop random effects but jointly estimate the three equations. Likewise, the results are similar to our main model.

Second, we reset the treatment and control group, i.e., non-adopters now serve as the treatment group and app adopters as the control group. We then conduct a PSM again by using nearest neighboring matching with ratio equaling 2 and without replacement. This step generates 435 matched customers, i.e., 145 non-adopters in the treatment group and 290 adopters in the control group (for the performance of PSM, see Appendix C). Similarly, we organize these customers' order records as monthly balanced panel data and re-estimate three equations. The results are similar to the main model.

Conclusions and Implications

The present study contributes to contemporary research on multichannel and mobile marketing in two ways. First, we examine how adding an app influences purchase behavior of customers who have shopped through a mobile website previously, which has not been discussed yet. This research set-up is relevant and interesting because apps and mobile websites, as search and purchase channels, have highly similar and also significantly different attributes. From the perspective of channel differences, the relative advantage of apps over mobile websites is the potential to attract customers to engage more with retailers and further improve customer spending at a focal retailer. Looking at channel similarity, adding a similar channel tends to cannibalize purchases in existing channels (e.g., Avery et al. 2012). In addition, the marginal benefit created by the new (similar) channel probably is weaker than the cannibalization effect in existing channels, thus leading to a total negative effect on customers' spending and retailers' revenue. Therefore, it is not clear whether a newly added app could induce more customer purchases for retailers who already have a mobile website. Our result shows that the newly added app indeed cannibalizes the existing mobile website in terms of customer spending (i.e., purchase frequency and order size). However, we also provide strong evidence for positive effects of an app on customers' total spending. Customers who adopt the newly added app are not only more likely to purchase, but also buy more frequently and spend more in each order than non-adopters.

Overall, our results reveal that app adoption does have a strong positive effect on customers' future spending. In effect, the app in our case is less comprehensive regarding its features if we compare it to popular and frequently-used apps such as Amazon's and Taobao's apps. For example, the app neither opens customer comment areas nor provides a recommendation system, which aims to offer effective, efficient, and personalized recommendations to individuals based on their historical data of browsing and purchasing. We believe that these functions would engage customers even more and further strengthen the app's positive impact on customer spending.

Second, we explore how the newly added app influences customers differently by involving two moderators, i.e., the spending share of different product categories and customer loyalty. Existing literature has not sufficiently discussed app adoption's divergent influence related to customer heterogeneity yet. Our results reveal that apps create stronger positive effects for customers with lower spending share of high-price products and less loyal customers, although the significant moderating effects are only found for order size. There is no well-documented work showing that apps are perceived as securer than mobile websites to the best of our knowledge, but our finding firstly suggests that apps are more influential for risk-averse customers. However, this is only supported for financial risk, not for the performance risk of products. The moderating impact of spending share of credence product is not significant. This is probably because the way how customers access product information through apps and mobile websites is very similar, e.g., through texts and videos. An app itself cannot reduce customers' perception of whether a specific product will perform properly per se. Besides, different risks show distinct implications for consumer behavior (Lutz and Reilly 1974) and could lead consumers to have different and independent perceptions (Mandrik and Bao 2005). Thus, it makes sense that one type of risks may dominate other types of risks in a specific situation. Our findings of spending share of high-price and credence products indicate that financial risk could be a dominant risk that consumers are concerned with when they choose mobile channels to purchase. The negative moderating effect of customer loyalty indicates that adopters with higher loyalty to a focal retailer purchase less in each order than customers with lower loyalty. Intuitively, loyalty customers would purchase more because they trust the retailer (e.g., Chaudhuri and Holbrook 2001) and are more willing to try a new channel. However, we show that apps lead to lower increase in order size for highly loyal customers than less loyal customers. We think this is a signal for a ceiling effect, i.e., the attractiveness of apps' advantages is higher for non-loyal customers than that for loyal customers. Our results also suggest that apps have the capability of attracting non-loyal customers to purchase more and thus potentially cultivate their future loyalty.

In summary, the positive effect of app adoption on customers' spending is strongly supported both for the purchase incidence and actual purchases. Apps also lead to larger order size for customers with lower spending share of high-price products and less loyal customers. Although a mobile website is the first step for retailers who want to try to get into mobile commerce due to its easier operation and lower investment in most cases, apps would create more value. Apps' benefits are not only derived from spurring purchases after their release, but also from its capability of mitigating perceived risk and fostering loyalty, which enhances customers' intention of continuing the relationship with retailers and thus creates more future profits.

Limitations and Suggestions for Future Research

We close by pointing out the limitations in our study, which provide avenues for further research. First, we do not have much demographic information of customers; rich demographics could be adopted to predict the possibility of app adoption and thus address the self-selecting issue in a better way. Second, we only use one dataset from a single retailer in China to test our hypotheses. The retailer in our case offers a well-designed mobile website and an app with basic functions but without advanced features like automatically recommending products according to customers' search and purchase history. This is a typical context for retailers who add an app to an already established mobile website. However, we acknowledge that the product categories we study are bought relatively frequently. The question is whether our findings would also hold for less frequently purchased goods and durables as well as services. Datasets from other industries are likely to provide more insights. For example, our findings suggest that apps cannot mitigate customers' perceived performance risk of a specific product. Thus, products requiring higher involvement such as furniture and cars are not suited to be sold in apps. Future studies on consumer app behavior for such durable goods, but also services would be required. Furthermore, our study should be executed in other countries. Chinese consumers are heavy mobile users and could be more used to apps, and in other countries this may be different. Whereas multiple limitations exist, we believe our findings can be generalized to countries with a strong mobile presence and to product categories that are frequently purchased. Still of course more research is required to provide to test our findings in other contexts. Third, we only use proxies from the transactional data to reflect customers' risk perception and loyalty. Future studies could measure such variables directly and combine survey data with retailing data to provide further support for our findings. A fourth limitation is that our method to correct for self-selection, does not account for biases due to forward looking behavior, which may arise because consumers who anticipate more purchases in the future are more likely to adopt the app than consumers who do not anticipate more purchases. However, one could argue that this bias is not as severe as the bias caused by customers' behavioral history (e.g., previous spending, previous tenure). A customer knows how much convenience s/he can obtain from the app only after s/he used the app. Before using the app, customers might not have accurate anticipation of app convenience and thus might not link their anticipated spending to adopting the app. Still PSM cannot completely solve the selecting bias but reduce the bias to a lower or an acceptable degree. The performance of our PSM is quite good (standard bias is smaller than 0.05), which means that the PSM here already reduces the bias to a lower level. Besides, previous studies (e.g., De Haan et al. 2018; Kim et al. 2015; Wang et al. 2015) also employ the similar method to reduce self-selecting issue.

Multiple follow-up questions are worth considering. First, apps do create profits for retailers, but they also need continuous investment to update, enhance, and maintain. So, one prevailing question is when retailers will obtain a positive net margin from a newly released app. Second, only Kim et al. (2015) discuss the effect of apps' features on consumers' purchase behavior; our research indicates that apps do stimulate consumers' purchases. More studies are needed to document how customers use specific features of apps and how these features contribute to customer loyalty and profit. Third, our main findings suggest that app adopters value apps' interaction, user-friendly interfaces, multiplatform settings, etc. Hence, the question arises whether these advantages will make customers less price sensitive, or will customers become more price sensitive because apps are more convenient for comparing prices? Further research should address these issues to refine and extend our knowledge in mobile apps and related consumer behavior. Finally, more research on app adoption is certainly required given some very recent evidence of Gu and Kannan (2018), that in contrast with many other studies app adoption may actually have negative effects on purchase behavior.

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Appendix A. The Survey of Customers' General Risk Perceptions in the App and Mobile Website

We conducted a simple survey only with three one-choice questions and one open-ended question to provide evidence for our argument, i.e., apps are perceived less risky than mobile websites to purchase. The survey was provided at the platform wjx.com (an open website for online surveys) in China on April 24, 2018 for 14 hours; almost all of participants (99.56%) filled in the survey though the mobile web link.

We collected 459 questionnaires, 50.54% of which are female. In the total sample, 57.08% of participants agree that apps are less risky than mobile websites to purchase and only 2.83% think the other way around. There are 21.13% of participants perceive that apps and mobile websites have similar risk levels, 18.95% of participants think the comparison of risk levels between the two channels is indefinite. We also asked participants to write down the reasons for their risk perceptions if they are willing to do this. At the end of the survey, there were 131 participants providing their specific reasons. The most mentioned reasons of “Apps are less risky than mobile websites” include: (1) apps are strictly censored by app stores before being released to customers, while mobile websites do not need censorship, (2) apps' operation has a particular platform, which can guarantee retailers' credibility to some extent, (3) it is easier for phishing sites to imitate and attack mobile websites than apps, (4) platforms (e.g., Android, iOS) of apps provides closed environments for purchasing; apps are independent systems. The reason of “Apps and mobile websites have similar/equal risk levels when purchasing” is mainly that both the two channels are virtual and without physical stores, so that they both have the risk of information/ data breach. Some participants also think that the two channels operate in the similar way at one's smartphone, so they share the similar risk levels. Some other participants think that the comparison of the risk level in the two channels depends on the security of apps' background programs and their development teams.

The following is the questionnaire we used:

移动渠道购买风险感知

大家好！我是中国科学院大学&格罗宁根大学的学生刘欢，以下问卷仅用于科学研究，您的信息及回答将被严格保密！以下问卷仅包含三个选择题项，可在一分钟之内完成，感谢您的参与！

1. 您的性别 *

- ○ 女性
- ○ 男性

2. 您的年龄 *

- ○ 18岁以下
- ○ 18-25岁
- ○ 26-30岁
- ○ 30-40岁
- ○ 40-50岁
- ○ 50岁以上

3. 在移动渠道购物过程中，您更同意以下哪种表述？ *

- ○ 移动app上的购物风险小于手机网页购物的风险
- ○ 移动app上的购物风险大于手机网页购物的风险
- ○ 移动app上的购物风险和手机网页购物的风险差不多
- ○ 移动app上的购物风险和手机网页购物的风险大小比较是不确定的

4. 如您愿意，请简要描述您做出以上选择的理由

提交

The following version is translated from the Chinese version for readers' convenience:

A.1. *Perceived Purchasing Risk in Mobile Channels*

Dear participants, I am a PhD candidate in the University of Groningen and the University of Chinese Academy of Sciences. The following survey is only used for academic research, and your information and answers will be strictly confidential. The survey only has three one-choice questions and one open-ended question, which can be completed in 1–2 minutes. Thanks so much for your participation!

1. Your gender

o. Female
o. Male

2. Your age

o. Younger than 18 years old
o. Between 18 to 25 years old
o. Between 26 to 30 years old
o. Between 30 to 40 years old
o. Between 40 to 50 years old
o. Elder than 50 years old

3. When you purchase products/services in mobile channels (i.e., apps, mobile websites), which the following statement do you agree?
o. Apps are less risky than mobile websites to purchase
o. Apps are more risk than mobile websites to purchase
o. Apps and mobile websites have similar/equal risk levels when purchasing
o. The comparison of risk levels in apps and mobile websites is indefinite.

4. Could you please write down your reasons for the choice in the third question if you are willing to do this?

Appendix B. Complement to the Main PSM

Table B1
Estimates of propensity score in the logit model.

Dependent Variable	Is an App Adopter (*Adopter*)	
	Coef.	p-value
Constant	2.874	0.42
1 ln(Tenure + 1)	0.487	0.56
2 ln(Recency + 1)	−0.374	0.00
3 ln(Number of orders + 1)	−2.566	0.03
4 ln(Spending + 1)	−0.007	0.99
5 ln(Customer_density + 1)	−0.346	0.41
Interaction 1*4	−0.051	0.66
Interaction 3*4	0.287	0.04
Interaction 1*5	0.061	0.50

Note: Log likelihood = −313.069; McFadden = 0.023; Likelihood-ratio test: p = .01; Hosmer-Lemeshow C-statistic = 0.920; Hosmer-Lemeshow H-statistc = 0.213.

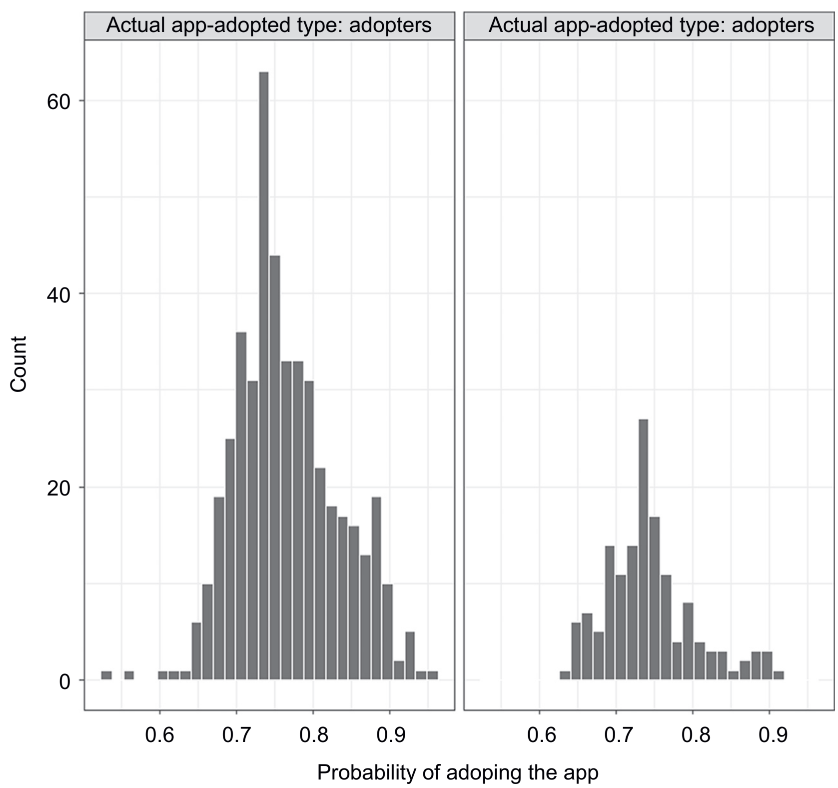

Fig. B1. The region of common support between the treatment and control group.

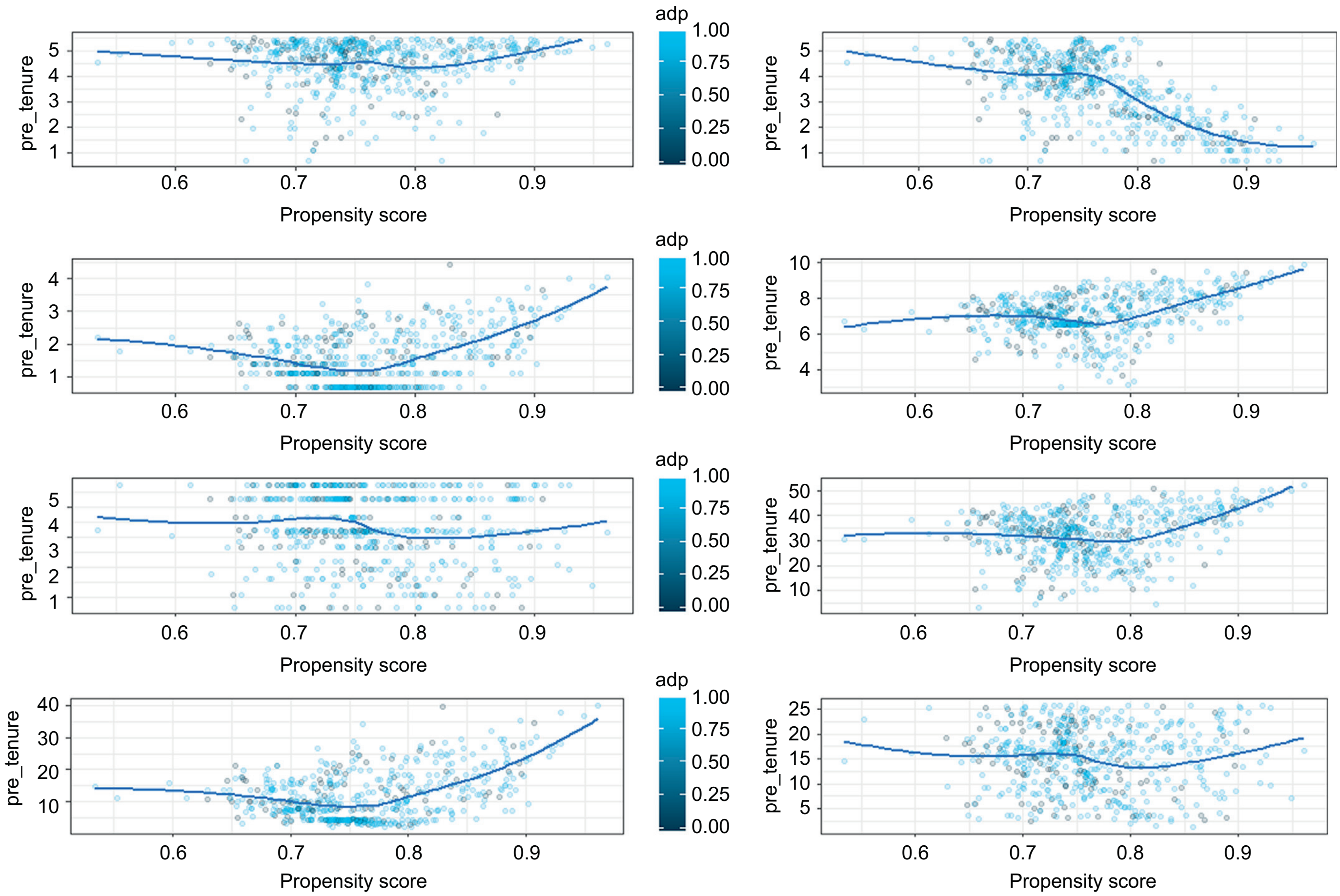

Fig. B2. The covariance balance in the matched sample. Note: It plots the mean of each covariate against the estimated propensity score, separately by treatment and control statuses.

Appendix C. Results of Robustness Checks and the Related PSM

Table C1
Results of robustness checks.

	Main model		Robust 1		Robust 2		Robust 3[a]	
Method	RE, joint		RE, separate		No RE, joint		RE, joint Treat group: non-adopters	
Purchase incidence model								
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Adp	0.406	0.00	0.401	0.00	0.392	0.00	0.434	0.00
$PI_{i,t-1}$	0.588	0.00	0.592	0.00	0.659	0.00	0.408	0.00
ln(Tenure+1)	−0.071	0.07	−0.063	0.10	−0.057	0.09	−0.051	0.32
ln(Recency+1)	0.035	0.29	0.030	0.37	0.026	0.37	−0.002	0.97
ln(Average order size +1)	0.035	0.34	0.042	0.24	0.041	0.21	0.001	0.98
Propensity score	1.244	0.01	1.158	0.02	1.050	0.01	−1.154	0.07
ln(Number of orders+1)	0.152	0.02	0.144	0.02	0.138	0.02	0.136	0.04
SS.highprice	0.082	0.06	0.067	0.69	0.066	0.67	0.018	0.90
SS.credence	0.015	0.92	0.015	0.91	0.018	0.89	0.088	0.59
Adp* ln(Number of orders+1)	0.057	0.38	0.061	0.34	0.056	0.34	0.051	0.46
Adp* SS.highprice	−0.192	0.29	−0.186	0.30	−0.183	0.27	−0.062	0.74
Adp* SS.credence	0.167	0.30	0.161	0.31	0.150	0.30	0.200	0.22
Purchase frequency model								
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Adp	0.147	0.00	0.221	0.00	0.144	0.00	0.220	0.00
ln(Tenure+1)	−0.045	0.02	−0.061	0.00	−0.045	0.01	−0.068	0.00

Table C1 (*continued*)

	Main model		Robust 1		Robust 2		Robust 3[a]	
ln(Average order size +1)	−0.040	0.16	−0.032	0.24	−0.043	0.12	−0.024	0.46
Propensity score	0.403	0.10	0.577	0.01	0.348	0.13	−0.412	0.16
ln(Number of orders+1)	0.085	0.11	0.121	0.02	0.082	0.01	0.118	0.02
SS.highprice	−0.075	0.63	−0.045	0.77	−0.074	0.63	−0.015	0.92
SS.credence	−0.013	0.92	−0.002	0.98	−0.012	0.92	0.013	0.91
Adp* ln(Number of orders+1)	−0.033	0.54	−0.043	0.42	−0.041	0.44	−0.032	0.56
Adp* SS.highprice	0.106	0.51	0.068	0.67	0.116	0.47	0.040	0.80
Adp* SS.credence	0.149	0.27	0.183	0.17	0.153	0.25	0.140	0.30
Order size model								
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Adp	0.221	0.00	0.248	0.00	0.171	0.01	0.236	0.00
ln(Tenure+1)	0.009	0.86	−0.013	0.81	−0.005	0.88	−0.071	0.24
ln(Recency+1)	0.015	0.71	0.024	0.61	0.051	0.10	0.085	0.11
ln(Average order size +1)	0.243	0.00	0.267	0.00	0.219	0.00	0.146	0.01
Propensity score	0.113	0.18	0.222	0.74	0.594	0.21	−0.607	0.42
ln(Number of orders+1)	0.166	0.05	0.174	0.05	0.171	0.02	0.217	0.01
SS.highprice	0.586	0.01	0.556	0.02	0.544	0.01	0.610	0.00
SS.credence	0.075	0.69	0.065	0.75	0.165	0.32	0.100	0.57
Adp* ln(Number of orders+1)	−0.215	0.01	−0.196	0.03	−0.232	0.00	−0.218	0.01
Adp* SS.highprice	−0.529	0.03	−0.504	0.05	−0.425	0.05	−0.571	0.01
Adp* SS.credence	0.055	0.79	0.018	0.94	−0.062	0.73	0.096	0.64

Note: Constants in the models of robustness check are omitted; the variances and correlations of random effects and error terms in the third robustness check are also omitted to save space.

[a] To achieve the convergence, we only allow the correlation of random effects across the three equations; no correlation of error terms is allowed.

Table C2
Summary statistics and covariate comparison before and after matching: reverse treatment and control groups.

Covariates: Pre-period behavioral characteristics	Treatment group: Non-Adopters (1)	Control group: Adopters		Difference-in-mean		Standardized bias	
		Before matching (2)	After matching (3)	Before matching (1)–(2)	After matching (1)–(3)	Before matching	After matching
1 ln(Tenure+1)	4.511	4.536	4.500	−0.024	0.012	0.027	0.013
2 ln(Recency+1)	3.725	3.428	3.712	0.296	0.013	0.249	0.011
3 ln(Number of orders+1)	1.465	1.564	1.464	−0.099	0.001	0.136	0.001
4 ln(Spending+1)	6.959	7.096	6.975	−0.137	−0.016	0.130	0.015
5 ln(Customer_density + 1)	3.387	3.328	3.412	0.059	−0.025	0.049	0.021
Interaction 1*4	31.705	32.534	31.667	−0.829	0.038	0.095	0.004
Interaction 3*4	10.778	11.852	10.819	−1.074	−0.040	0.157	0.006

Note: 145 non-adopters in the treatment group and 460 adopters in the control group. The nearest neighboring matching method was adopted with the ratio of 2, without replacement. The PSM generates 435 customers in total, of which 290 adopters are matched with 145 non-adopters. The standard bias of all covariates after matching is smaller than 0.05.

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