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What's in Your Mobile Wallet?

Purchase Effects of Downloading versus Adopting Branded Apps on Digital Payments

Abstract

Mobile payment methods and apps are key technologies, but managers are often unsure of their ultimate business impact. This research differentiates micro-payments with SMS carrier billing from app-based mobile wallets and quantifies how much and when the latter increases spending at physical transaction locations. We integrate observational, survey, and experimental studies to demonstrate that branded app mobile wallets (BAMWs) both reduce payment awareness and are easier to use than carrier billing option (CBO) payments, which increases customer spending in transaction data. For a beverage brand sold in vending machines, covariate-balancing propensity score matching and difference-in-difference-in-differences methodology analyze changes in purchase amounts and frequencies across three types of mobile payment customers: CBO payment only, CBO payers who download the app but never switch to its mobile wallet, and BAMW users. The adoption of mobile wallet functionality more than doubles postadoption purchase amounts in the month after the adoption, with overall purchase amounts remaining 25% higher in the long run and purchase frequencies remaining 8% higher for mobile wallet adopters than nonadopters. The effect of adopting mobile wallet functionality is much stronger than the effect of only downloading the branded app. Moreover, these effects are heterogeneous, with the mobile wallet adoption effects being stronger for recent adopters and overall app adoption effects being stronger for light and medium buyers. These insights into the adoption of branded mobile apps show that it is not the download of the branded payment app that matters, but whether consumers use its BAMW instrument.

Keywords: mobile payment, app, mobile wallet, pain of paying, multiple treatments matching, covariance-balancing propensity score, difference-in-differences, natural experiment, fast-moving consumer good, vending machine

1. Introduction

Digital payments and, in particular, mobile payments have surged globally in recent years, as the world moves toward cashless societies. As of 2017, one-third of Internet users worldwide had "used a mobile payment service in the last month," with forecasts projecting more than 1.1 billion proximity mobile payment users worldwide by 2021 (Statista 2019). By 2022, payments for goods and services with a mobile device are forecast to exceed £3.5 trillion globally and surpass the use of cash and credit cards (Allied Market Research 2018, Worldpay 2018). WeChat Pay and Alipay report more than 1 billion daily active users, while Apple Pay, Amazon Pay, Google Pay, and Starbucks Pay are estimated to exceed 383, 50, 24, and 23 million users, respectively (MerchantSavvy 2019). Companies are rushing to link consumers to their mobile payment instruments (Wang et al. 2016). However, mobile payments differ strongly in terms of consumer experience, from sending SMS, which does not require a credit card but increases phone bills in the carrier billing option (CBO), to dedicated payment apps in branded mobile wallets, which are convenient and seamless but require preregistering a credit card, owning a smartphone, and being willing to download the retailer's proprietary app. Moreover, developing and promoting new mobile payments are also expensive for brands. Therefore, a vital managerial question is: How does branded mobile app adoption affect customers' purchase behavior? Specifically, does mobile wallet adoption increase overall purchase amount and frequency? If so, does the company benefit from the branded app download or from the adoption of the mobile wallet functionality? Finally, does the impact of new forms of payment depend on the length of customer tenure and the speed of app adoption?

Unfortunately, the literature does not answer these questions, and research calls abound to provide managers with clearer insights into the impact of mobile shopping and mobile payments on consumer behavior (Dahlberg et al. 2015, Shankar et al. 2016, Faulds et al. 2018). In particular, little is known about the impact of different mobile payment methods on purchase behavior. Existing research has either focused on mobile app design and drivers of consumer adoption of mobile apps (typically applying the technology acceptance model framework to the mobile setting) or empirically evaluated the effects of mobile use on purchases (Dahlberg, Guo & Ondrus 2015), but it has not investigated how different forms of mobile payment instruments ultimately affect sales.

In this study, we measure the causal impact of adopting branded app mobile wallet (BAMW) payments on purchase behavior of mobile payment adopters who have previously adopted CBO payments. We distinguish the purchase lift from the download of the branded app versus the adoption of new payment (mobile wallet) functionality. The distinction is relevant for companies that, like our data provider, mostly focus on promoting app downloads instead of stimulating use of the mobile wallet functionality. To this end, we enrich causal inference methodology by using nonbinary treatment estimations, covariate-balancing propensity scores (CBPSs), and difference-in-difference-in-differences (DDD) analysis. We show that the use of this approach provides significantly richer insights and prevents incorrect conclusions.

For a leading, international beverage brand sold in vending machines, DDD methodology reveals that adoption of BAMW payment increases both purchase amounts and frequency, compared with CBO purchase baselines. The week after mobile wallet adoption, purchase amounts are 143% higher and remain 20% larger for the mobile wallet group compared with CBO purchases. The frequency of purchases increases by 35% in the week after mobile wallet adoption and remains 7% higher in the long run. By contrast, downloading the app but not switching to the mobile wallet option (continuing instead to use CBO payments via the app) has a substantially lower effect, increasing purchase amounts by 11% and purchase frequency by 3%. Therefore, the purchase effect of BAMW is not primarily the function of the app but rather the mobile wallet functionality. Of note, CBO purchases do not decline, indicating that the purchase lift does not reflect cannibalization but rather the greater excitement and better payment experience consumers report in our survey.

We also demonstrate important moderators to the average effect, showing the heterogeneity on the treatment effect sizes. The effects of BAMW adoption become stronger for more recent adopters (customers who adopt the mobile wallet option most recently), most likely due to habit formation of early adopters over time. While light and medium spenders show a somewhat greater propensity to adopt the app in general, we find no significant differences in the impact of adopting the mobile wallet between heavy and light spenders (for both groups, we find a strong positive impact of BAMW adoption). This is consistent with our survey findings that both major types of mobile payments have their respective advantages and identifies past behavior-based customer segments that companies can target with appropriate messages to help increase BAMW adoption and, in turn, company benefits.

This research makes three distinct contributions. First, we use a multimethod approach to understand and test the causal impact of consumers' choices between downloading and using various types of branded app-based mobile payments to purchase. The combination of secondary data, a customer survey, and a lab experiment enables us to derive conclusions on the reasons behind consumers' choices. Second, we assess the effect of mobile payments in a physical setting, in which we show how consumers adopt digital instruments in a physical environment. Third, our study is one of the first to analyze the impact of different mobile payment instruments. Thus, this research contributes to the payment and app adoption literature by quantifying the benefits of application-based mobile payment downloads and usage over time and to the practitioners by showing the monetary benefits of mobile payment apps.

2. Research Background

2.1. Types of Mobile Payments

Mobile payments are "payments for goods, services and bills with a mobile device by taking advantage of wireless and other communication technologies" (Dahlberg 2015, p. 265). They allow cashless and contactless payments at a point-of-sales station, kiosk, or vending machine through a mobile device thanks to barcodes/QR codes or near-field communication technology. The two main types of mobile payments are sending short message service (SMS) with CBO, in which customers can buy products and services by sending a SMS via a mobile phone, and mobile (digital) wallets, which store payment card information on a mobile device, typically in an app (Sorensen 2018). Both types of mobile payments have their strengths and weaknesses, but evidence is scarce on how consumers perceive these. On the one hand, CBO payments leverage consumers' familiarity with SMS systems, but they entail CBO fees and require consumers to loop through several steps in the process. On the other hand, mobile wallets allow payments with a direct tap, reducing the steps in the payment process, and do not entail CBO fees, but rather require customers to register their credit card details.

While CBO payments have traditionally dominated mobile payment services, adoption rates of app-based payments with mobile wallets have surged, with these payments representing the fastest-growing mobile payment option (Mobile Payments Today 2018a, Juniper Research 2019, Stone 2020). Mobile wallets are often associated with Google Wallet and Apple Pay systems, but the most popular BAMW in the United States is Starbucks' (eMarketer 2018). While both apps and mobile shopping have received recent research attention, little is known about their combination and the impact of the adoption of mobile (app) payments on consumer purchase behavior; even less is known about BAMW services.

2.2. Literature on Mobile Shopping and the Effect of Mobile Payments

Mobile e-commerce and mobile shopping have received substantive attention in the literature. Initially, the research focus centered on understanding the drivers of adoption and use of information technology in general and mobile technology in particular, drawing on the technology acceptance model (Davis 1989) and the unified theory of acceptance and use of technology (Venkatesh et al. 2012). In general, these studies show that the intention to use mobile technology is driven by customers' perceptions of its expected benefits and costs (Hew et al. 2015).

On the perceived benefit side, novel payment methods may ease the hassle and pain of paying, as they make the actual payment less salient (as verified in our customer survey). Research on the pain of paying suggests that paying with an instrument that is less tangible (than cash) reduces the perceived pain of paying, as the depletion of resources is less visible (Prelec and Lowenstein 1998). Reduced pain of paying increases customer spending (Soman 2001, Prelec and Simester 2001). Although little evidence exists on the pain of paying for mobile payment methods in particular, Ariely and Silva (2002) suggest that micro-payment methods (i.e., small payments that require specific confirmation, as in SMS payments) increase the salience of the payment and also the pain of paying. In addition, the CBO/SMS payment method incurs higher costs. Therefore, with the reduced pain of payment and more seamless payment experience, we expect BAMW payments to have a stronger impact on customer purchases.

Regarding branded apps, several studies show their positive impact on brand attitudes and brand responses, increasing interest in the brand and the brand's product category (Stocchi et al. 2017, Kim and Baek 2018). Nevertheless, the effects depend on the design and intended function of the app, with informational apps (those with utilitarian functions such as purchasing) having a stronger impact on purchase intention and cognitive brand responses (Bellman et al. 2011, Taylor and Levin 2014, van Noort and van Reijmersdal 2019). As the payment function offers utilitarian benefits to consumers, adoption of a mobile payment app may enhance brand engagement. These studies, however, offer little insights into what motivates customers to use the technology after adoption or the impact of adopting a branded app on subsequent purchase behavior.

The impact of mobile apps on actual customer behavior shows mixed results, with varying definitions of mobile shopping or app payments, as we summarize in Table 1. First, announcements of app launches with transaction-oriented features (facilitating purchase) either decrease firm value (Boyd et al. 2019) or increase it (Cao et al. 2018). Second, for purchase, using mobile devices at any stage of the online shopping funnel increases online orders (Wang et al. 2015), but purchase conversion drops when customers switch from other devices (e.g., desktop) to a mobile device (De Haan et al. 2018), and app adoption decreases spending (Gu and Kannan 2018). Finally, cannibalization of other payment channels is low (Huang et al. 2016) or nonexistent (Einav et al. 2014), while Xu et al. (2017) show that introduction of the tablet shopping option cannibalizes online purchases through the PC channel but acts as a complement to the smartphone channel.

---- Insert Table 1 about here ----

In summary, our literature review shows mixed findings on the company benefits of mobile app payment adoption, and little empirical evidence reveals the effects of different payment features such as mobile wallet or SMS/CBO payments. As Figure 1 shows, our study resides at the intersection of three research streams: app adoption, mobile payment instruments, and the pain-of-paying psychological mechanism.

--- Insert Figure 1 about here ----

2.3. Moderators of the Effects of Mobile Payments

Two main types of moderators can affect the impact of mobile payments on purchase behavior: the pre-adoption purchase level and the timing of adoption (early vs. late adopters). Li et al. (2015) find that adoption of an online channel increases purchases of light shoppers but does not significantly affect purchase of heavy shoppers. Similarly, Wang et al. (2015) show that adoption of m-shopping especially increases order rate and order size for low-spending customers. Einav et al. (2014) find that mobile adopters are heavier spenders than nonadopters on average, indicating that self-section based on usage levels may occur for mobile app adopters. They also show that the adoption impact becomes more pronounced for early mobile app adopters. Conversely, Gu and Kannan (2018) find that the negative effects of app adoption are more pronounced among early adopters than those who adopt later. To reconcile these diverse findings and account for customer differences in adoption effects, we need to consider the moderating impacts of preadoption purchase levels and endogenous adoption timing.

3. Empirical Setting, Data, and Studies

To examine the impact of different types of mobile payments on consumer behavior, the ideal setting would be a country whose customers are familiar with cashless payments and the use of mobile phones in commercial settings. Norway has one of the lowest cash usage rates in the world, with less than 10% of customers using cash, only 6% of sales value being generated with cash, and cash point-of-sales transactions amounting to less than 11% (European Payments Council 2018). With one of the highest gross domestic product per capita in the world and almost universal smartphone penetration, Norway is also among the countries with the fastest adoption of mobile payments. In 2017, Norwegians executed approximately 90 million mobile phone payments (European Payments Council 2018).

Therefore, the transactional data for this study come from a leading international beverage brand with its own network of vending machines in Norway. These vending machines sell diverse types of beverages by this retailer and are located in different public and business areas. This brand is one of the early adopters of mobile payments in retail setting, introducing *CBO-based mobile payments* for vending machine purchases in the fall of 2012. As a standard feature, vending machines allow for debit-/credit-card and cash purchases, to which the new mobile payment options were added (first CBO-based payments, then the app-based payment option). This order of payment introduction is the typical path most companies use, due to technological developments in the mobile payment landscape: barcode/QR code reading and near-field communication, which allows for proximity payments at the point of sales (Mobile Payments Today 2018a).

The rollout of the CBO-based payment system across vending machines occurred within a few weeks after launch, during which the number of machines with mobile payment options steadily increased. The main promotion of the new CBO-based payment system was on the vending machines themselves with a sticker indicating that CBO payments are possible, with instructions and a phone number that buyers must use to complete the purchase. CBO mobile payers have to complete several steps in the process of purchasing using the CBO option. First, they must register their accounts on the platform of an external operator (owned by a major telecom provider). Second, the payment is processed when customers send an SMS message with specification of the vending machine, product, and amount to a phone number, and the amount is charged through the CBO (i.e., with purchased amounts added to a monthly phone bill). This type of purchase entails a CBO fee that amounts to approximately 15% of the price of an average product in the assortment.

Eighty-seven weeks after introducing the CBO-based mobile payments, the brand launched a *branded mobile payment app*, which featured a *mobile wallet* payment option (allowing for contactless, cashless payments at vending machines with a tap on a mobile phone). A prerequisite for using the mobile wallet is registration of a payment card (debit/credit card) in the app. The app also allows customers to access the SMS payment platform that we previously described. One reason to do so is convenience, as some of the information required for the CBO transaction is prefilled. Still, the consumer needs to pay the CBO fee and undertake several steps in the CBO transaction process. Figure 2 depicts the cumulative adoption curves of CBO versus mobile wallet adopters. As the figure shows, the CBO payment option had a higher adoption rate than the mobile wallet option, indicating that cannibalization is not a major issue, consistent with previous research (Einav et al. 2014, Huang et al. 2016),

---- Insert Figure 2 about here ----

The main promotion of the BAMW was through the information on the vending machines, on which a sticker with the payment app option was added (next to the information on how to purchase with the SMS option without the app). In addition to the featured advertising on the vending machines, the retailer promoted the new app at a Norwegian university, in which new app customers were given a free Coke for downloading the app. We control for these events in our model. Likewise, we control for app system failure and app adjustments in our model.

According to the data provider, sales through vending machines increased with the new payment options, which led us to examine whether those purchases were due to the app adoption or novel forms of payment instruments[1] (i.e., BAMW). We proceeded to critically examine whether consumers indeed perceived the proposed advantages of the new payment option. As the unified theory of acceptance and use of technology (Venkatesh et al. 2012) holds that the perceived benefits and costs are critical to adoption, we want to better understand the attitudes of mobile payers relative to standard payers (those who pay with debit or credit cards). To do so, we use a multimethod approach of observational, survey, and experimental studies.

3.1. Observational and Survey Study of Mobile Phone versus Nonphone Payers

At a large Norwegian university, we observed and surveyed university students (a key target audience according to the data provider). During a regular day at the beginning of December 2018, six groups of research assistants observed 124 purchases at different vending machines and coffee shops at the university. At these places, 13.8% of payments were by a mobile phone, while the remaining 86.3% were by bank cards or cash (cash or a voucher was used in 5.6% of purchases). For convenience, we refer to all non-mobile payments as card payments. After buying their products, buyers were approached by the

[1] All vending machines allowed for credit-/debit-card purchases, but due to the Norwegian data protection policy, the retailer cannot obtain the full credit card credentials on those transactions. Therefore, it is not possible for the retailer to match individual purchases through other channels (direct credit card purchases and cash) with purchases through mobile payments. Because cash is seldom used in Norway (less than 10% of customers use cash for payments in retailing), the share of cash option payments is small. In our analysis, we therefore focus on the impact of introducing new app-based forms of mobile payments on customers who have already adopted mobile payments (i.e., those who have used CBO payments and subsequently adopted BAMW or app-based SMS payment).

research assistants and asked to respond to a survey. They were asked about their satisfaction with the items bought, payment process, and payment experience and their perceptions of a series of statements related to payment options. Given differences between the phone and nonphone payment samples, we used independent-samples Mann–Whitney (U) nonparametric tests and the two-samples Kolmogorov–Smirnov test to analyze the between-group differences.

We found no significant differences between mobile phone and card payers in the level of satisfaction with the product bought ($M_{phone} = 5.65$ vs. $M_{card} = 5.64$; $U = 797.5$, $p = .395$) or payment process (5.53 vs. 5.84; $U = 874$, $p = .783$) on a seven-point Likert scale. Moreover, there were no significant differences between phone and card payers in perceptions of feeling secure about the payment transaction just made (6.24 vs. 6.14; $U = 905$, $p = .972$). Importantly, compared with card payers, phone payers perceived mobile phone payments as more convenient ($M_{phone} = 5.94$ vs. $M_{card} = 4.29$; $U = 365.5$, $p = .000$), faster ($M_{phone} = 5.35$ vs. $M_{card} = 4.35$; $U = 570.5$, $p = .012$), easier to pay with ($M_{phone} = 5.31$ vs. $M_{card} = 4.42$; $U = 571.5$, $p = .030$), more fun ($M_{phone} = 5.29$ vs. $M_{card} = 4.30$; $U = 558$, $p = .009$), and marginally cheaper ($M_{phone} = 3.78$ vs. $M_{card} = 4.24$; $U = 692.5$, $p = .078$). When asked with open-ended questions about their reasons for payment preference, phone payers indicated the convenience of payments and avoiding having to carry a wallet/card as main drivers of the choice. Similarly, the card payers stated that they use the card for convenience and out of habit. There were no statistically significant differences at the 95% confidence level between the two groups when asked about the perceived novelty of the payment option. Both phone and credit-card payments were not considered particularly novel ($M_{phone} = 3.29$ vs. $M_{card} = 2.59$; $U = 659$, $p = .053$).

3.2. Lab Experiment on Pain-of-Paying Differences Between Payment Modes

To avoid making causal claims based on the observational study (as payers self-select into their preferred mode of payment), we conducted a lab experiment to explore the pain of paying between the mobile payment method and the typical bank card method. The act of paying is commonly associated with an aversive feeling described as the "pain of paying" (Prelec and Loewenstein 1998) or "payment salience" (Soman 2001, 2003), which makes people aware that they are spending (parting with) money. The extent to which this emotion is felt depends on the form in which the payment is made (Prelec and Simester 2001, Raghubir and Srivastava 2008). Less transparent means of payment (in our context, phone versus cash or credit card) generate less pain than transparent forms of visible spending, such as cash (Soman 2001, 2003). As such, willingness to pay should increase with the less transparent mode of payment (Prelec and Simester 2001).

Two-hundred forty respondents (62% female; mean age 24.2; mean disposable monthly income approx. US $212) at a large Norwegian university completed this study for a payment of approximately US$10. The respondents were presented with a scenario of purchasing a branded soft drink (Coke) for themselves and for a friend during a break between lectures in a nearby vending machine (for details, see Appendix). The respondents were randomly assigned to either a bank card payment condition or mobile app payment condition. In addition, we primed the type of purpose for which the payment is used so as to understand how mobile phone versus card usage types affect the pain of paying. The results show no statistical differences in perceptions of payment convenience, speed, or easiness or security of paying between respondents in the two conditions. Our main interest is the perceived pain of paying for the soft drink with the bank card versus the mobile app. We operationalized perceived pain of paying with a standard item from the literature (Shah et al. 2016) on a seven-point scale (1 = not at all painful, 7 = extremely painful): "It was painful to think about paying for my friend's Coke." We used the scenario in which the respondent pays both for him- or herself and the friend to make the payment situation more salient than individual taste preferences alone. In addition, we primed the purpose of the phone use (we asked respondents to write down five situations in which they use phone/card for personal or social use purposes). The transparency (salience) of the payment should be lower when the social purpose of using the phone is primed compared with personal use.

As Figure 3 illustrates, we find that respondents perceive paying with a mobile app on a vending machine as less painful than paying with a bank card ($M_{phone} = 2.99$ vs. $M_{card} = 3.50$; $F = 4.470$, $p = .035$). Moreover, the interaction between the prime type and payment type is significant ($F = 5.079$, $p = .007$). The mean pain of paying for a socially primed use of phone is significantly lower than that for a socially primed use of credit card (1.73 vs. 2.71, $p = .006$). Therefore, compared with bank card payments, mobile payments reduce the perceived pain of paying, particularly when consumers think of the social use of payment instruments.

----Insert Figure 3 about here ---

In summary, our observational and survey studies show that, compared with card payments, paying with a mobile phone increases convenience, speed, and perceived ease of use. The experimental study shows that the differences between payment modes can be explained by the reduced pain of paying with the phone versus a credit card. This finding of reduced pain of paying, coupled with the increased perception of convenience and easiness of paying for those who select mobile app payment, suggests that mobile payment apps can increase purchases of mobile app adopters. We now turn to establishing the causal impact in the customer data.

3.3. Transaction Data Analysis: Launch of App-Based Mobile Payments

The original transaction data include more than 152k customers from which we selected the final dataset for this analysis using two criteria. First, the customer purchased at least twice, such that at least one purchase occurred before the launch of the branded payment app and one occurred after the launch. These criteria exclude one-time trials and all only-before or only-after purchases. Second, the data have the full set of observables about customer descriptives (e.g., zip code, age), when the customer first adopted CBO-based payments, and whether and when the app payments were adopted/made. This selection resulted in a sample of 9903 customers who used CBO-only payments and never adopted the app during the 212 weeks of observation, 1643 customers who used CBO payments in the period before the app launch and who downloaded and registered the app but never used BAMW (i.e., continued CBO-app purchases), and finally 380 customers who used the CBO option in the pre-launch period and adopted BAMW payments.[2] This early adoption rate of BAMW payments of 3.3% is in line with reports showing mobile wallet adoption

[2] We coded customers as mobile wallet payers if they paid with the mobile wallet in the observation period. Only 67 customers never use CBO after adopting the app (using CBO purchases, e.g., if the app experiences technical problems). In this strict sense, we are comparing nonmobile wallet adopters with mobile wallet adopters who may act as multichannel payers, having expanded the number of payment channels they use.

rates between 3 and 4% (PYMNTS 2017). Figure 3 shows the model-free evidence on the average weekly purchase amounts before and after the week of app adoption for CBO-only payers, CBO payers who downloaded the app but did not adopt the BAMW, and mobile wallet payers.

---- Insert Figures 4a and 4b about here ----

The first set of model-free evidence comes from the differences in average purchase amounts and frequencies between CBO payers and mobile wallet users. Figure 4 shows the average purchase amounts and frequencies over 212 weeks of observation data for CBO payers and payers who eventually adopted the mobile wallet. The initial weeks show substantive fluctuations (due to the relatively low number of purchases in the initial period). The figure shows that the average weekly amount of purchases among mobile wallet adopters was initially lower than that of the CBO payers. However, this trend ultimately switches after the BAMW launch, and both the average purchase amount and frequency of mobile wallet payers exceed those of the CBO payers. On average, CBO payers in the prelaunch period purchase more frequently (2.34 vs. 2.08 times per week) and spend more (scaled data results 36.1 vs. 32.1) than mobile wallet payers. However, in the postlaunch period, CBO-only buyers spend less and purchase less frequently than mobile wallet adopters (2.37 vs. 2.62 and 42.2 vs. 47.5, respectively).

4. Method

4.1. Identification Strategy

Figure 4, as well as the changes in purchase amounts and frequencies, suggests that the adoption of the BAMW had a positive impact on users' subsequent purchase behavior. However, the increase in purchase behavior could be due to factors other than the adoption of the BAMW. First, it may be that the best customers (those who are the mostly likely to increase their purchases over time) self-select into adopting the mobile wallet. In this case, it is the type of customers adopting the mobile wallet and their lifetime trajectory of purchases, rather than the mobile wallet adoption per se, that caused the purchase increase. Second, other forms of prelaunch differences between CBO-only payers and mobile wallet payers may also prevent us from attributing the increase in purchases to the right cause. For example, customers living in more urban areas may be more inclined to adopt novel technological solutions than those in rural areas or less affluent city areas. To control for endogeneity bias from self-selection of customers into the preferred mode of payment and other unobserved systematic biases, we analyze the data using the difference-in-differences approach, matching customers on their observable prelaunch characteristics such as purchase behavior, zip code, and the time of first adopting the CBO payment. In essence, we want to estimate the difference between the average purchase amount and frequency of BAMW adopters and those of CBO-only payers in the periods after the branded-mobile payment app was introduced, controlling for differences between the two groups that cannot be attributed to the adoption of the BAMW (Lechner 2011). To control for the exogeneous variables that may lead to differential trends between CBO-only adopters and mobile wallet adopters, but are not influenced by the decision to adopt mobile wallet, we match customers with similar observed characteristics in the prelaunch period (e.g., prelaunch purchase frequency and spending, when customer first adopted mobile CBO payments, zip code, last purchase week, gender, age).

Furthermore, to differentiate between the causal effects of adopting the app and those of adopting the BAMW, we differentiate between three groups of customers: (1) those who have initially adopted CBO payments but, in the postlaunch period, never registered for the app and continued purchasing through the CBO option (*CBO-only*); (2) those who initially adopted CBO payments and downloaded and registered the app but never adopted (registered and used) the mobile wallet option (*CBO-app*); and (3) those who initially adopted CBO payments before the launch of the app and subsequently adopted and purchased with the BAMW (*Mobile Wallet*). In the terminology of causal inference models, the treatment condition is the mobile wallet condition, while the two forms of CBO payment conditions serve as control conditions for the impact of adopting the branded app versus mobile wallet (CBO-app condition) and for the impact of a new type of mobile wallet payment versus the traditional CBO payment option (CBO-only).

4.2. Comparison of Treated and Control Groups

The comparison between the mobile payer groups that over time have adopted different forms of payment begins with the description of their behavior before the launch of the branded mobile payment app. We excluded customers for whom we could not obtain user characteristics from the analysis. Table 2 shows the average mean differences in the prelaunch period of the app-based payment system across the three groups when no purchase per individual customers is taken into account.

---- Insert Table 2 about here ----

To attain a better picture of the possible matching characteristics of customers, we coded the zip code of the vending machine that the individual phone user used most often. Because many vending machines are located in specific areas (e.g., university unions, local shopping malls), it is likely that customers with similar characteristics use the vending machine at a certain location (e.g., students at a university, employees at a certain organization, locals at a shopping mall). We use the zip code locations of vending machines throughout Norway (note that Norway is a scarcely populated country with large distances between cities). In the capital and major cities, we could pinpoint the exact location of each vending machine and used this information to further group customers. In this way, we identified 18 dummies to code location (counties/zip codes) in the dataset and used this information for matching.

Next, customers choose when to join the CBO and BAMW, and therefore it is important to control for the date of their adoption of these and the potential stoppage of usage during the observation period. This is particularly relevant for the purpose of matching, because adjusting the entry and activity windows between the treated and matched control customer, across all three groups, is important. Therefore, we use the month of joining and a recency of activity (last week with purchases) indicator (se Datta et al. 2018).

5. Model Specification

Table 3 summarizes the model challenges and how we address them. To account for self-selection of customers into multivalued treatments (challenges 1 and 2), we estimate a covariance-balancing generalized propensity score for multivalued treatments that models treatment assignment while optimizing the balance of covariates (Imai and Ratkovic 2014). Next, using the estimated propensity score, we match customers from the three groups into triplets. After creating the triplets, to account for the endogenous nature of adoption timing, we assign the pre-/posttreatment periods of the BAMW customers to the matched CBO-only and CBO-app customers to ascertain whether the triplets have the same pre- and post-app adoption observation window (challenge 3). Finally, we apply a two-way fixed-effects panel regression in the DDD framework to estimate the average treatment effect of adopting the BAMW payment instrument, while controlling for the impact of adopting the branded app (challenge 4).

---- Insert Table 3 around here ----

5.1. Propensity Score Matching for Multivalued Treatments

Customers self-select which payment to use and may inherently differ on many dimensions. The gold standard for causal inference would be random assignment of payers in a controlled experiment. As that is not possible in this case, we used the Rubin causal model approach to infer the causal impact of payment app adoption on outcomes of customer behavior based on observational data (Athey and Imbens 2017). The standard approach is to estimate the conditional probability of belonging to each group (i.e., receiving the treatment)—that is, the propensity score (Rosenbaum and Rubin 1983). An unbiased estimate of the treatment effect can be obtained by adjusting for the propensity score rather than matching directly on a high dimension vector of customer characteristics (Imai and Ratkovic 2014). This implies that propensity scores can be calculated as the probability that a customer receives the treatment (adopts different payment instruments) conditional on his or her observable characteristics (before the launch of the app).

In practice, much of the causal impact literature focuses on binary treatments. Applied to this case, this would mean measuring the impact of adopting (vs. not adopting) the app (Kim et al. 2015). Despite the relevance of accessing treatments at multiple levels, limited theoretical and empirical work exists on multivalued treatments (Athey and Imbens 2017). Propensity score estimation from binary treatment cases cannot be directly extended to multivalued treatments, because there is no scalar function of the covariates that has the same properties as in the binary case. Accordingly, the researcher cannot use two binary propensity scores to replace a multivalued propensity score (which would amount to matching based on different logistic regressions). Therefore, Imbens (2000) introduced the generalized propensity score, showing that for multivalued treatments, generalized propensity scores can be calculated as the multinominal probabilities (e.g., from a multinominal logistic regression; Imai and Ratkovic 2014).

Finally, the main practical difficulty of using propensity scores is that their slight misspecification leads to a substantial bias of estimated treatment effects (Kang and Schafer 2007, Imai and Ratkovic 2014). The relationship between propensity score estimation and covariates is "paradoxical in nature because the propensity score is designed to reduce the dimension of covariates and yet its estimation requires modelling of high dimension covariates" (Imai and Ratkovic 2014, p. 244). Therefore, Imai and Ratkovic (2014) propose estimating the CBPS, which at the same time models treatment assignment without consulting the outcome data and optimizes covariate balance. We use this approach for three main reasons. First, CBPSs are robust to potential misspecification that traditional parametric propensity score models are prone to because they need to select a propensity score that maximizes the resulting covariate balance. Conversely, CBPS in a single model determines both the treatment assignment mechanisms and the covariate balancing weights. Second, CBPS estimation can be extended to the multivalued treatments because a generalized propensity CBPSs can entail the multinominal probabilities of receiving different treatments (where all conditional probabilities sum to 1) (Imai and Ratkovic 2014). Third, CBPSs can be directly used for multigroup propensity score matching because of its dimension-reduction property. This is essential in our application to determine matched before and after periods across groups for DDD estimation of the impact.

Therefore, we used the generalized method of moments to estimate each customer's CBPS of being assigned to the one of the three groups (CBO-only, CBO-app, or Mobile Wallet) given the covariates (i.e., customer characteristics in the periods before launch of the branded payment app). The covariates used are the average (log) weekly purchase amount and frequency before the app launch divided by the tenure before the app in weeks from first joining the CBO, month of first joining CBO, zip-code-based location, last week of purchase. Variable operationalizations are provided in Table 4.

We evaluate model validity in two ways. First, we use Hansen's J-statistic to test for overidentifying restrictions. Its close-to-zero value (J = 0.000055) indicates that the propensity model is correctly specified and fits the data well. Second, we illustrate the CBPS balance optimization in box plots in Figure 5. The box plots show that the CBPS weighting estimation substantively improves the balance in covariates by reducing the differences in covariates across the three groups of customers. Similarly, Table 2 shows an overview of the customer descriptives in the matched versus unmatched sample.

----Insert Table 4 and Figure 5 about here----

5.2. Finding Matched Triplets Using the CBPS

Because the CBPS produced generalized propensity scores for all three groups, we can now use these scores to find the matching triplets in the multivalued treatment. Following the recommendation of Imai and Ratkovic (2014), we used the CBPS to match triplets through two matching logistic regressions. Applying exact matching on the weeks of joining and last purchasing and CBPSs, we used one-to-one nearest-neighbor matching to retain the closest matching triplets. We used *exact matching* on the month of joining the CBO option in the periods before the app was introduced and the last purchase week. We also used *approximate matching* based on the recency (proxy by last observed purchase in the dataset), length of relationship before launch of the app, area of living, purchase amounts and frequency in the period before the app was introduced. Moreover, as mentioned previously, to be selected for analysis, customers had to have at least two purchases, one before and one after the app launch in week 87. To reduce the impact of attrition, the last purchase also must have occurred after week 120 (of 212 weeks). For robustness, we also estimated the alternative matching approach (Bryer 2017), which uses multinomial regression to create matched triplets by minimizing the total distance between matched triplets within the caliper. The final estimations of the difference-in-differences effects were not substantively different, so we proceeded with Imai and Ratkovic's (2014) approach because it yields relatively more usable triplet matches (370 vs. 298). The final propensity scored matched sample of 370 triplets (1110 customers) compares well with 394 twins in Kumar et al. (2016) and 231 twins in Datta et al. (2018).

In the next step of our method, for each triplet we identified the week in which the mobile wallet payer adopted the BAMW payment. The weeks before and after this endogenously defined adoption time become the before and after periods for each payer in this triplet. Using the standard approach, we coded this indicator variable as 0 for the before periods and as 1 for the after periods. Based on the matched sample, Figure 6 provides model-free evidence of purchase amounts for the three groups of payers (triplets) in the weeks before and after mobile wallet adoption. Compared with the CBO samples, the payers who adopt the BAMW payment instrument show a strong peak in purchase amounts at the adoption period, and this remains higher than that of the other groups in the periods after adoption.

---- Insert Figure 6 about here ----

Table 5 lists the descriptive statistics of the main purchase variables across groups before and after matching when actual adoption time is taken into account. As the table shows, accounting for the endogenous timing of adopting the BAMW makes a significant difference in purchase averages across groups (vs. Table 2, which shows the general before and after periods relative to the app launch regardless of the timing of the app adoption).

---- Insert Table 5 about here----

5.3. Two-Way Fixed-Effects Panel Regression Analysis

We observe purchase behavior for up to 212 weeks of the observation period for 370 matched triplets in our sample. Therefore, we estimate the DDD panel regression, in which we evaluate the increase in weekly purchase amounts and frequencies due to the adoption of the BAMW payment instrument compared with the purchase trajectories of non-mobile-wallet adopters (CBO-app and CBO-only). We specify the model as

$$\boldsymbol{Y_{it}^{(Am,Fr)}} = \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} + \boldsymbol{\delta_{it} Post_{it}} + \boldsymbol{\lambda}(\boldsymbol{Post_{it}} * \boldsymbol{I_i^{CBOapp\ or\ MW}}) + \boldsymbol{\beta_{AW}}(\boldsymbol{I_i^{MW}} * \boldsymbol{Post_{it}^{AdoptWk}}) + \boldsymbol{\beta_{ST}}(\boldsymbol{I_i^{MW}} * \boldsymbol{Post_{it}^{AdoptWk+1}}) + \boldsymbol{\beta_{MT}}(\boldsymbol{I_i^{MW}} * \boldsymbol{Post_{it}^{(2 \le WksAfter \le 5)}}) + \boldsymbol{\beta_{LT}}(\boldsymbol{I_i^{MW}} * \boldsymbol{Post_{it}^{(WksAfter \ge 6)}}) + \boldsymbol{Z_{it}\pi} + \boldsymbol{\varepsilon_i} \quad (1),$$

where $\boldsymbol{Y_{it}^{(Am,Fr)}}$ is the natural logarithm of individual weekly purchase amounts (Am) or frequency (Fr), across both channels (CBO and Mobil Wallet). We estimate the two specifications separately. Next, $\boldsymbol{Post_{it}}$ specifies the postadoption periods based on the week of adoption of BAMW (0 in the weeks before adoption and 1 in the weeks after for all three members of the triplet, the BAMW adopter and the two control CBPS-matched CBO payers). The main parameters of interest (DDD effect estimators) are betas; they estimate the effects of the mobile wallet (MW) adoption (where $\boldsymbol{I_i^{MW}}$ is 1 for BAMW adopters and 0 otherwise) in the postadoption periods ($\boldsymbol{Post_{it}^{Adopt\ldots}}$). Following the approach of Datta et al. (2018), we explore the difference in the effect over time by creating 0/1 indicators for the impact on purchase patterns in the adoption week ($\boldsymbol{Post_{it}^{AdoptWk}}$), the short-term impact in the week after the adoption ($\boldsymbol{Post_{it}^{AdoptWk+1}}$), the medium-term impact within the first month after adoption ($\boldsymbol{Post_{it}^{(2 \leq WksAfter \leq 5)}}$), and the long-term impact after the first month of adoption (five weeks and more after the adoption; $\boldsymbol{Post_{it}^{(WksAfter \geq 6)}}$). The specification $\boldsymbol{\lambda}(\boldsymbol{Post_{it}} * I_i^{CBOapp\ or\ MW})$ captures the effect of adopting the app in the postadoption periods, regardless of whether the mobile wallet has been adopted (i.e., continuing to use the CBO payment instrument). This specification sheds more light on the impact of adopting the app in general and allows us to evaluate betas as the true impact of mobile wallet adoption (beyond the impact of adopting the app). We use two-way fixed-effects specification, where $\boldsymbol{\alpha_i}$ represents the individual customer fixed effects, $\boldsymbol{\gamma_t}$ specifies week-specific fixed effects, and $\boldsymbol{\varepsilon_i}$ is the error. Note that in Eq. 1, there is no need for other "main-effects" specification of the difference-in-differences variables, which would be fully collinear with the three temporal effects and fixed-effects specifications.

To avoid a biased estimation of the causal effects, specification of the difference between the "treatment" and "control" groups must be constant over time and potential parallel trends over time must be accounted for (Lechner 2011). We do this in three ways. First, in the vector Z we specify the control variables that may directly affect the purchase of drinks in vending machines over time: the weeks with marketing promotions, seasonal variables (Christmas and summer holidays), and weeks with known service failure of the app. Second, in addition to the prior matching procedure, which accounts for self-selection on observed characteristics, we specify a two-way within- (fixed-) effects panel estimation, where $\boldsymbol{\alpha_i}$ captures the fixed effects per individual to account for the unobserved heterogeneity between customers and $\boldsymbol{\gamma_t}$ captures weekly dummies to account for potential unobserved time variations (Bertrand et al. 2004). Third, we use a robust standard error correction of the Newey and West robust covariance matrix estimator for panel models with serial correlation to account for potential autocorrelation (Newey and West 1987, Zeileis 2004).

6. Findings

6.1. Main Effects

Table 6 shows the results of the DDD estimation for customer weekly purchase amounts and frequency (number of purchases). Compared with nonpayers, who never adopted the app or its payment options, the mobile wallet app adopters increased their purchase amounts and frequency in both the short- and long-term periods. In the short-term, a week after the mobile wallet app adoption, the purchase amounts of mobile wallet payers more than doubled (152% increase) and purchase frequency increased by 36%. In the medium-term, one month after adoption (from the second to the fifth week after adoption), mobile wallet adopters remain high at a 114% increase over the CBO-only baseline for purchase amounts and a 36% increase in purchase frequencies. Overall, in the long-term, in the postadoption periods until the end of the observation, the overall purchase amount remains 25% higher and frequency remains 8% higher. These numbers are in line with the 24% purchase amount increases in previous literature (e.g., Narang and Shankar 2016). Importantly, this increase cannot be attributed to the mere adoption of the app, but rather to the use of the BAMW payment instrument, because the explained effect nets out the adoption of the app. Table 6 also shows that the impact of app adoption is significantly weaker than the impact of BAMW adoption (6% for increase in purchase amount and 2% increase in purchase frequency). These general findings are robust across different specifications of the matching method (see Section 8). Finally, the large effect estimates in the week of adoption are likely due to the adoption of the BAMW when customers decide to purchase a product (i.e., standing in front of the vending machine).

---- Insert Table 6 around here ----

6.2. Moderators

The moderator analysis uses the interaction between the overall DDD effect in the postadoption period (without specifying short-, medium-, long-term indicators) and the median-split variable indicating whether, in the period before the app launch, the customer was a heavy spender (above the median spending amount) or not (below the median spending). Accordingly, we coded early adopters as those who adopted the app before the middle of the postadoption period (week 150). Following the approach of Datta et al. (2018), we specify a single treatment effect of adoption in the postadoption period ($Post_{it}$) that equals 1 on and after the week of adoption and 0 otherwise. Table 7 illustrates the differences across segments before and after adoption.

---- Insert Table 7 around here ----

We estimate the following DDD equations with moderating effects:

$$\boldsymbol{Y_{it}^{(Am,Fr)} = \alpha_i + \gamma_t + \delta_1 Post_{it} + \rho_1(Post_{it} * I_i^{CBOapp\ or\ MW}) + \varphi_1(Post_{it} * I_i^{MW}) + \mu_1(Post_{it} * I_i^{EarlyAdopter}) + \theta_1(Post_{it} * I_i^{CBOapp\ or\ MW} * I_i^{EarlyAdopter}) + \omega_1(Post_{it} * I_i^{MW} * I_i^{EarlyAdopter}) + Z_{it}\pi + \varepsilon_i.} \quad \textbf{(2)}$$

$$\boldsymbol{Y_{it}^{(Am,Fr)} = \alpha_i + \gamma_t + \delta_2 Post_{it} + \rho_2(Post_{it} * I_i^{CBOapp\ or\ MW}) + \varphi_2(Post_{it} * I_i^{MW}) + \mu_2(Post_{it} * I_i^{HeavySpend}) + \theta_2(Post_{it} * I_i^{CBOapp\ or\ MW} * I_i^{HeavySpend}) + \omega_2(Post_{it} * I_i^{MW} * I_i^{HeavySpend}) + Z_{it}\pi + \varepsilon_i.} \quad \textbf{(3)}$$

The main foci of interest are the $\boldsymbol{\omega_{1,2}}$ coefficients of the heterogeneous average treatment effects of adopting the mobile wallet among different groups of customers on purchase amounts and purchase frequency of those customers over time ($\boldsymbol{Y_{it}^{(Am,Fr)}}$). Specifically, in Eq. 2, $\boldsymbol{\omega_1}$ are the coefficients of the interaction term for the postadoption period for *early adopters* of BAMW (i.e., customers who adopted BAMW before the median week 150) compared with later adopters. In Eq. 3, $\boldsymbol{\omega_2}$ is the equivalent of the *heavy spenders* in the preadoption period who ultimately adopted BAMW (the heavy spending indicator equals 1 for customers whose sum of spent amounts over their tenure before the app launch is higher than a median of 2.26). Next, $\boldsymbol{\theta_{1,2}}$ explores the interaction effects for app adopters (both Mobile Wallet and CBO-app) and postadoption periods for early adopters and heavy spenders, respectively. We use effect coding for moderators (*early adopter* coded 1, and *later adopter* coded –1), because this allows us to interpret the average adoption effects for the app ($\boldsymbol{\rho_{1,2}}$) and mobile wallet ($\boldsymbol{\varphi_{1,2}}$), as well as the deviation from those effects for an above-median (vs. below-median) consumer. Table 8 shows the results of estimations of the heterogeneous treatment effects on purchase amounts and frequency for early versus late adopters and heavy versus light spenders in the prelaunch period.

---- Insert Table 8 about here ----

The average effects of adopting the BAMW payment option above and beyond the effects of adopting the branded app is .338 on purchase amounts and .113 on purchase frequency (40% and 12% increase over the CBO baselines, respectively). However, these increases are slightly lower for early adopters than later adopters (–.087 for amounts and –.025 for frequencies). The impact of adopting the app (but not the BAMW function) is also positive, but much weaker than the BAMW effect. On average, app adopters increase their purchase amounts in the postadoption period by around 5% and frequencies by 2%. However, while early adopters increase their purchase amounts even more than late adopters (.090), the increase in purchase frequencies is lower than that for late adopters (–.021).

Comparing the effects of app or mobile wallet adoption for heavy versus light spenders in the prelaunch period, we again find that the average effect of adoption of the BAMW payment is stronger than the average effect of app adoption (37% vs. 6% for amounts and 11% vs. 2% for frequency, respectively). However, we find no significant deviations from the average BAMW adoption effects between the previously heavy versus light buyers. Although app adoption has an overall positive impact on purchases, the increase is weaker than average for heavy spenders than light spenders (–.046 vs.–.016, respectively).

7. Substitution versus Complementarity Between Payment Types

We observe all mobile payment types in the database, both before and after the adoption of BAMW payments, which allows us to analyze the interplay between the two channels' purchases. We first note that 82% of BAMW adopters used the CBO option at least once after adopting the app. The data provider explained that BAMW payers used the CBO option in case of system failures or issues with credit card registration and the like. For the unmatched sample of customers, we analyzed weekly purchase amounts, separating CBO (either through app or directly) from BAMW purchases. For each individual and week combination, we distinguish whether the purchase was payed for with CBO, mobile wallet, or a combination (i.e., in the same week, the individual purchased using both CBO and BAMW instruments). Table 9 shows the average purchase amounts in total, for CBO payments, BAMW payments, and multichannel payments across the weeks in which these channels were used. Multichannel payments show the largest overall amounts, with about an equal contribution from CBO and BAMW payments.

---- Insert Table 9 about here ----

Next, we divided the overall weekly purchases per individual into two separate variables (BAMW_purchases and CBO_purchases). First, for the matched sample, we estimated the impact of lnCBO_purchases on lnBAMW_puchases per individual/week using a two-way fixed-effect regression with weekly CBO amounts, seasonality, and system failure indicators as control variables. We find no effects of CBO purchase amounts on BAMW purchase amounts (coef. = –.0004, SE = .0008). The effects of CBO purchase frequencies on BAMW purchase frequency is also close to zero but significant (coeff. = –.002, SE = .001). Therefore, we find no or a very weak cannibalizing effect of CBO purchases on BAMW purchases.

Second, for CBO purchases, we have both pre- and post-app adoption data, so we can run the full DDD equation on CBO purchases only, using BAMW purchases as either amounts or frequency, and on app purchase amounts and frequency (coef. reestimated DDD models for lnCBO_purchases as the main dependent variable and lnApp_purchases with other DDD variables in Eq. 1 as the independent variable). The resulting coefficients for CBO-only purchases in Table 10 show significant cannibalization of BAMW purchases on CBO purchases (around 5.4% on purchase amount and 6.4% on purchase frequency).

---- Insert Table 10 about here ----

In summary, we find that some substitution between channels occurs but the effects are asymmetric. While BAMW purchase amounts and frequency significantly affect CBO purchases, this does not occur the other way around. Still, we find that the strongest positive increase occurs for multichannel buyers who use both payment instruments.

8. Robustness Checks

We conducted several robustness checks to ascertain the relevance of our findings. First, we estimated placebo effect DDD regressions, in which we arbitrarily set the pre- /postlaunch periods to test the assumption of parallel (common) pretreatment trends (Lechner 2011). Following the standard convention suggested by Bertrand et al. (2004), we estimated DDD models for purchase amounts and frequency when setting the postlaunch effect indicator in the middle of the preadoption period (i.e., postlaunch effect indicator set to 1 for periods after week 44 [note that the launch of the app occurred in week 87 and 0 for periods before that week). As expected, the estimated DDD effects of adopting a mobile wallet app in such "placebo" treatment scenarios are nonsignificant. The DDD coefficient for the interaction between the app mobile wallet adopters and placebo posttreatment effects is .005 (corrected robust standard error .051; p = .915) for the effect on purchase amounts and .002 (corrected robust standard error .017; p = .924) for the effect on purchase frequency.

The second set of robustness checks dealt with the selection of customers who were included in the final analysis using the matching procedure. Therefore, we have estimated DDD models that used different types of propensity score matching. In the alternative approach, we create matched triplets by minimizing the total distance between three groups using the nearest neighbourd distances within the caliper (the distance must be within .25 of one standard deviation to be kept) with TriMatch package in R for Propensity Score Matching of Non-Binary Treatments (Bryer 2017). We used one-to-one nearest-neighbor matching with replacement to retain the closest matching triplets. We again applied exact matching on the date of BAMW adoption and CBPSs and used the logit function to create triplets. Similar to Imai and Ratkovic's (2014) procedure of finding matches in Section 5, this procedure estimates the propensity scores for each pair of groups (i.e., two treatments and one control). This method then iteratively attempts to find the best matched triplets based on minimizing the summed differences among propensity scores across the three models (Bryer 2017). The best balance with matching produced 298 triplets with the data characteristics presented in Table 11.

---- Insert Table 11 about here ----

The results of the DDD analysis on this robust sample, with the model specifications in Eq. 1, produced similar results to the findings presented in Section 6. The results presented in Table 12 again show that the main drivers of the increase in purchase amount and frequency occur from the adoption of the BAMW payment instrument. In this smaller sample, the estimated sizes are similar to those in Table 6, confirming the robustness of the model. Placebo effect estimations on the robustness check sample again show nonsignificant DDD effects, confirming our previous findings.

---- Insert Table 12 about here ----

9. Discussion

Despite consumers saying they intend to use mobile wallets (Mobile Payments Today 2018b), adoption and purchase boosts are uncertain (Rooney 2019). Having quantified the purchase increases from download and use of the BAMW, we can now answer our research questions for the beverage brand under study. Yes, BAMW adoption increases overall purchase amount and frequency, though the benefit decreases over time from the adoption week. Importantly, benefits to the company mainly stem from BAWM use (i.e., adoption of the mobile wallet functionality), not the mere act of downloading the branded app. Finally, the purchase increase due to BAMW adoption is strong and positive for all customers, but the increase is even more pronounced for more recent than early adopters of the BAMW. This result is consistent with the findings of Gu and Kannan (2018), who observe stronger positive effects of app adoption for later than earlier adopters.

For the overall app adoption, the positive impact is stronger for light users (lower-than-median purchases before app adoption), likely because of the likelihood to increase their purchase amount over the baseline. Likewise, Wang et al. (2015) find that using mobile phones (vs. PCs) increases purchase amounts and frequency especially for low-spending customers. Of note, we do not find significant differences in purchase increases between heavy and light buyers due to BAMW adoption, as both groups show a strong positive impact. These findings relate to the literature on online channel and app adoptions. For example, Li et al. (2015) find that adoption of an online channel increases purchases in the light shopper segment but does not significantly affect purchases of heavy shoppers.

In terms of the conceptual development, these findings enrich both the theory and empirical evidence on the acceptance and use of new technology, in particular BAMW payment instruments. First, the observational study and lab experiment show that the mechanism is indeed reduced pain of paying, not the lower price itself, and that prospective users care about fun and convenience. Second, our analysis of the transaction data show that, compared with the CBO baselines, purchase amounts for BAMW users increase 19 times more in the week of adoption, decrease to 1.5 times more the week after adoption, and then remain higher by 25% on average in the long run. By contrast, the effect of users downloading the app but not using its mobile wallet functionality is much weaker (6% increase in amounts and 2% in frequencies). Thus, the acceptance (app download) and use of new technology (its new functionality) should be distinguished conceptually and empirically. Most of the previous studies of data adoption effects on purchases attributed the full effect to the app adoption (cf. Table 1), in case of the mobile payment apps, these effects are conflated. We show that the mere adoption of the app and switching to its more convenient use of CBO functionality does not change the behavior to a large extent. This could be due to the nature of CBO purchasing, which is more cumbersome and less convenient than contactless, cashless payment options. Finally, we expected the greater purchase increase for fast adopters from theory, as adoption speed indicates both preference and urgency for the new technology. However, the stronger impact for light users demonstrates the unlocked potential of customers not fully satisfied with the existing payment technology.

From a methodology standpoint, our study deals with several challenges not often addressed in managerial and economics literature. The first issue is the prevalent use of binary treatments even when multivalued treatments occur in reality. Distinguishing between the levels of treatment is crucial for attributing the purchase increase to the adoption of the branded app versus its mobile wallet functionality. Matching multivalued treatment groups on separately estimated binary propensity score models is inappropriate (Lechner 2001, Linden et al. 2016). Novel advances in multivalued treatment propensity score estimations should be employed on a larger scale in managerial studies, as multiple treatments often occur in practice, such as the staged adoption of functionalities and/or solutions provided by the focal firm. Second, matching on the basis of propensity score estimation has weaknesses, due to the iterative process of finding a balance between observed covariates and model fitting of treatment assignment (Imai and Ratkovic 2014). We therefore use CBPSs that optimize the covariate balance while modeling the treatment assignment and, in this way, improve the balance of observed covariates regardless of whether there are unmeasured confounders. Finally, compared with the often-used application of difference-in-differences analyses in economics, in which the treatment is exogenously given by, for example, the implementation of government policy, in marketing and management studies the moment of adoption is endogenously decided by the customer or firm. In this context, we show that it is important to use endogenously defined before/after periods in difference-in-differences based on the actual date of adoption, rather than the general periods before and after launch of the app. Our study shows that such an analysis would resemble a placebo effect estimation, in that for most of the mobile wallet adopters, it would wrongly include the before-actual-adoption periods in the posttreatment effects.

10. Limitations and Future Research Avenues

This study shows how consumers perceive *different* forms of mobile payments and how their adoption of BAMW increases purchase amount and frequency as compared with consumers who stick with CBO. The research is unique in terms of its triangulation of observation, survey, a lab experiment, and a causal analysis of actual customer behavior in field data. Moreover, it is among the first to estimate nonbinary (multivalues treatments) CBPS matching and generate DDD estimation of the effects of (1) downloading the BAMW versus (2) using its mobile wallet functionality at physical (vs. virtual) locations. In doing so, the study reveals the limited benefits of mere app downloads, a focus of both previous research and the company's marketing efforts. Instead, consumer adoption of the mobile wallet functionality substantially increases both purchase amount and frequency. The survey and lab experiment show specific ways the company can induce such adoption—with a focus on fun and reduced pain of paying, instead of only price and convenience. The stronger purchase impact for customers with limited previous purchases (light users) also helps companies target audiences for maximum benefit.

Several limitations offer opportunities for future research. First, the field data did not allow a customer-level investigation of the decision to adopt the CBO, as the company only began collecting data from that time onward. Likewise, privacy laws and considerations prevented linking the survey with the field data for a specific customer. Second, future research is necessary to verify the generalizability of our findings beyond one brand, one country, one category, and one period. Regarding the brand, we note that the percentage of customers adopting the company's BAMW is similar to that reported in the business press. For the country, Norway is second in general mobile wallet adoption (42% vs. 47% in China), so the current findings may foreshadow upcoming developments in other countries with large potential, such as the United States (Stone 2020). Infrastructure, cultural, and economic differences between countries may speed up or slow down app adoption and success (Kübler et al. 2018), a fertile area for future research. For the category, we analyze purchases in a frequently bought, low-risk convenience category of soft drinks. For the period, we explore the effects of contactless, cashless payments before the coronavirus pandemic. We surmise that contactless, cashless payments have increased in appeal since the start of the pandemic and that the impact of adoption may have increased further from the pandemic.

Finally, mobile payment methods continue to evolve, with the possibility of novel solutions that will allow merging information from payment devices, phones, wearables, and loyalty program data. Nevertheless, understanding of the underlying psychological motivators is lagging behind these advancements. In hybrid solutions that combine many functions, the salience of payment, novelty, pain of paying, and convenience heuristics are all intertwined, so new insights into these drivers and their interactions are welcome.

In conclusion, researchers and managers should carefully consider the perceived benefits of different mobile payment options and differentiate app downloads from use in terms of their impact and opportunity to stimulate with marketing actions. As the results show, it is not the download of the branded app that is important but whether consumers use it.

Figure 1. Combining Research Streams of App Adoption, Mobile Payment, and Pain of Paying

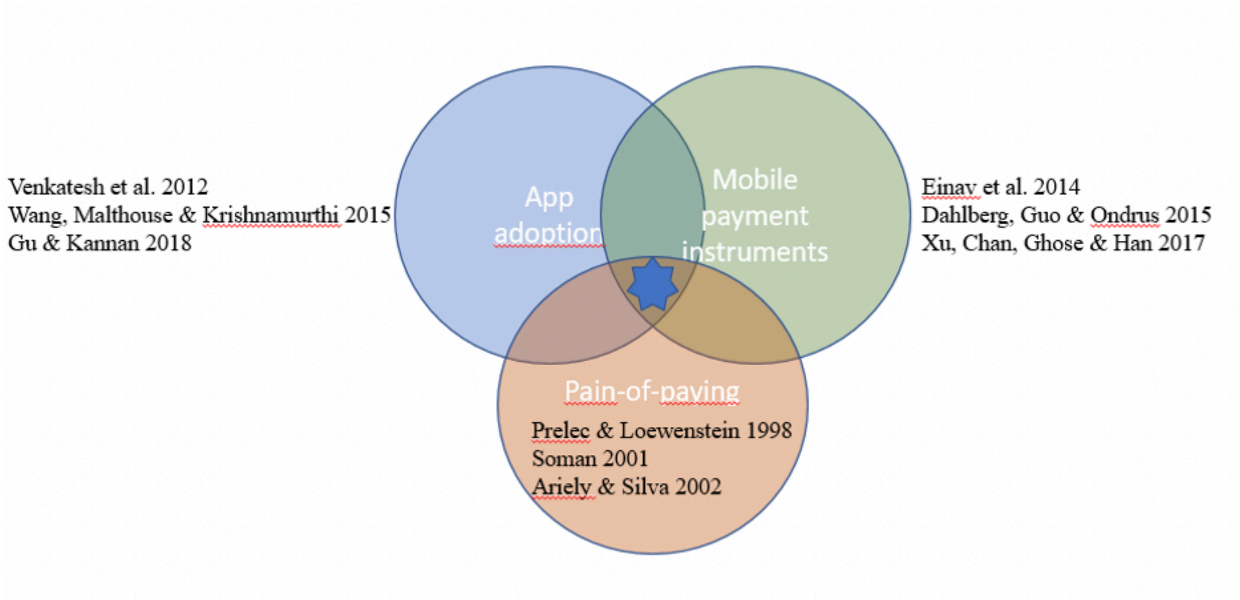
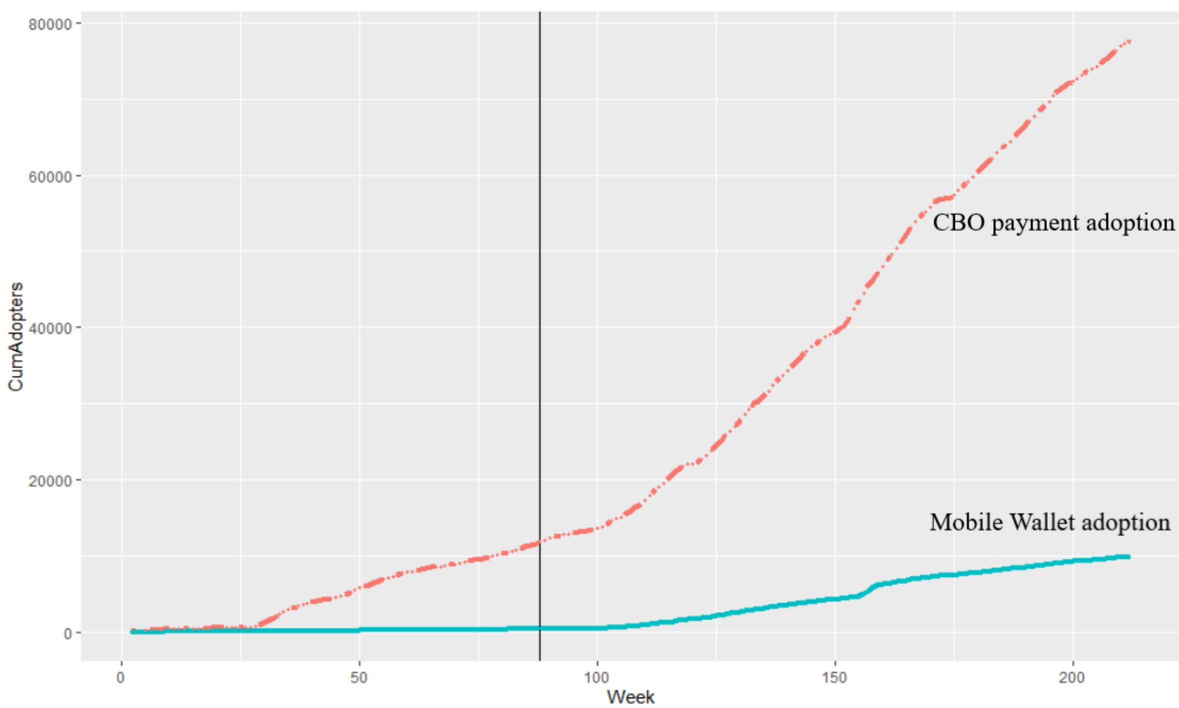


Figure 2. Cumulative Adoption Trends for CBO versus BAMW



The graph shows cumulative rate of adoption of CBO and mobile wallet from the moment of the first introduction of mobile payment options on vending machines. The vertical line represents the introduction of the mobile payment app, which featured mobile wallet (predominantly) but also allowed CBO users to access the platform via the app. The cumulative number represents the number of new adopters in a week. Ultimately, 3% of customers adopted mobile wallet, which is in line with market reports from similar payment apps, for the first year and a half after launch of the mobile wallet.

Figure 3. Experiment Results on Pain of Paying Between Mobile and Card Payments

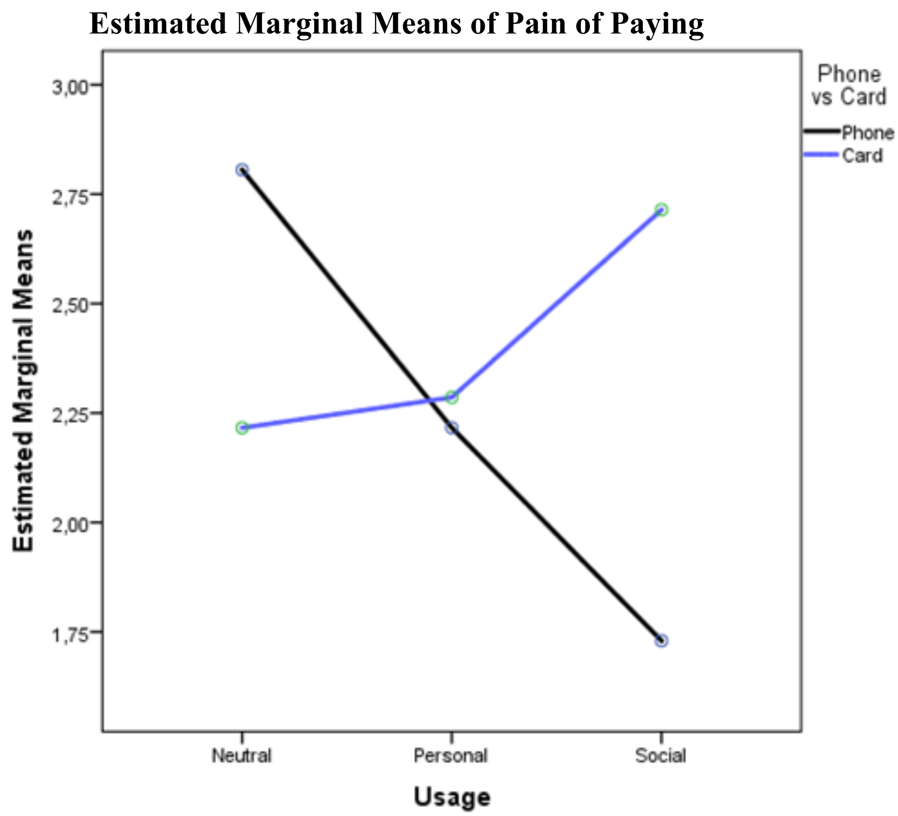


Figure 4. Average Weekly Purchase Frequency (4a) and Amount (4b) for CBO (Dotted Line) and BAMW Payers (Solid Line)

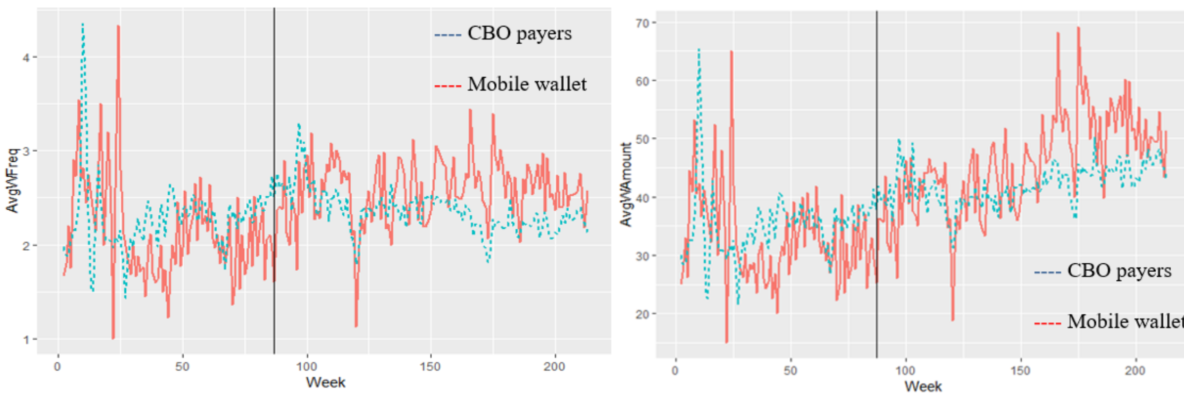


Figure 5. Box Plots of Absolute Differences in Covariates across three Groups Before and After Balancing Optimization with CBPS Estimation

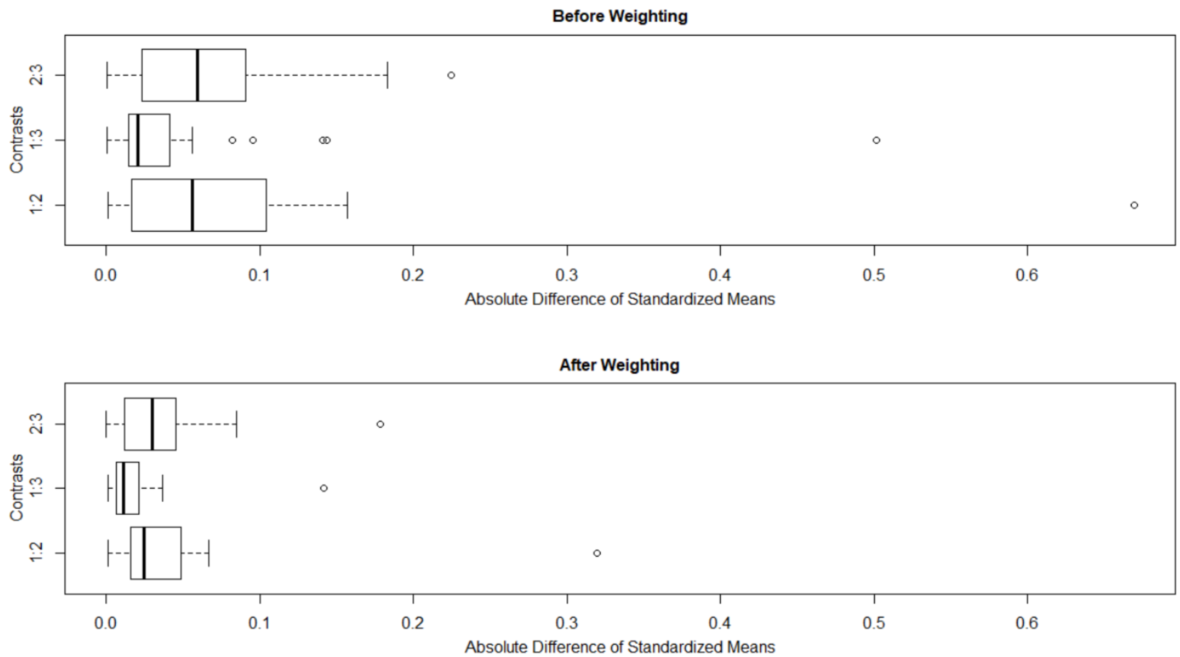
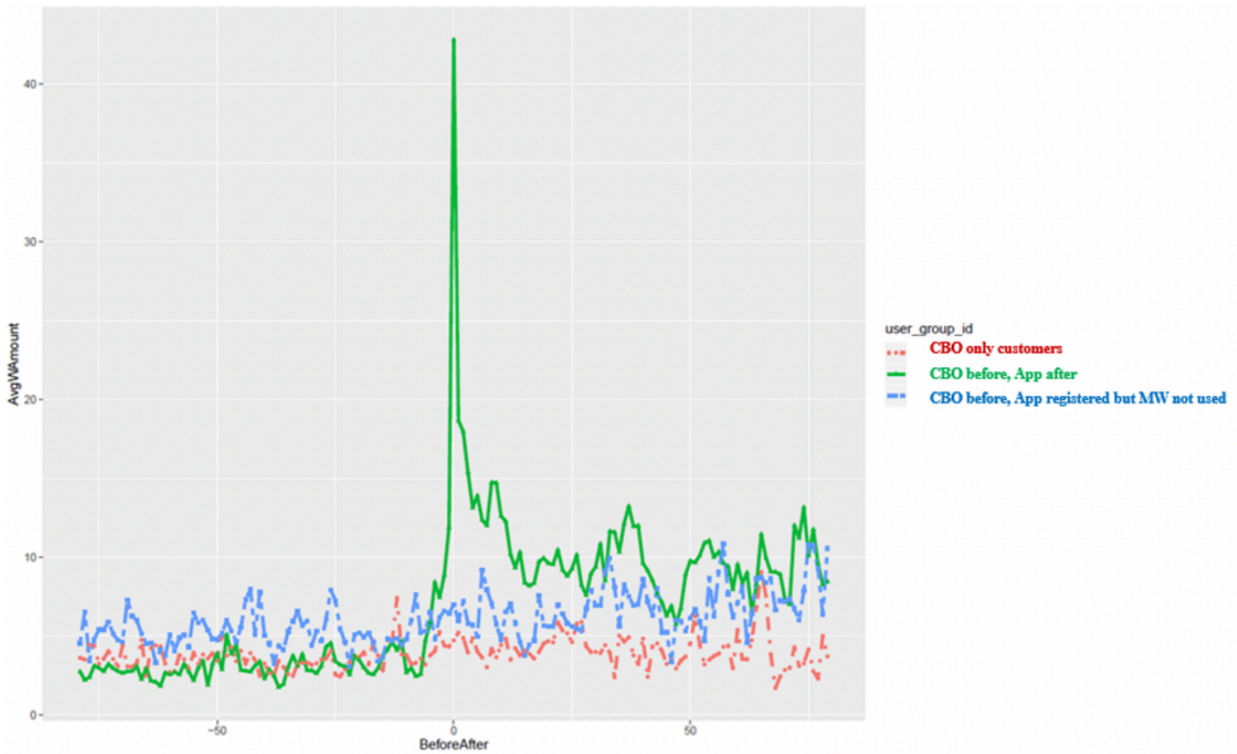
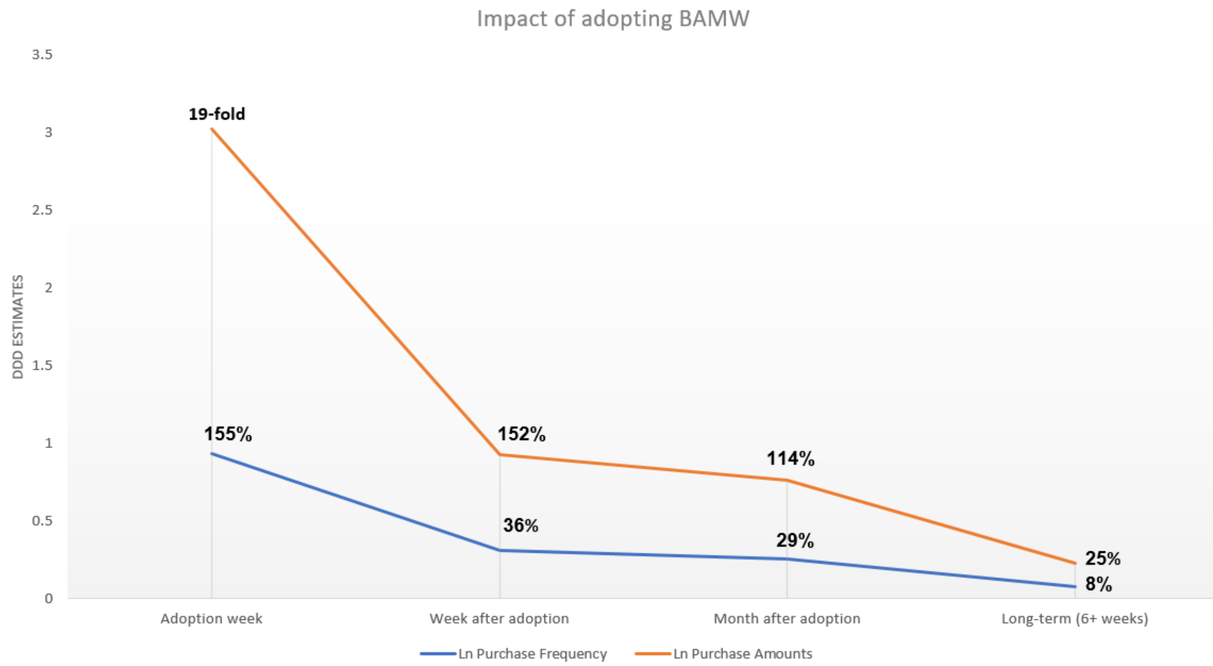


Figure 6. Model-Free Evidence of Individual Purchase Amounts on Periods Before and After Branded Payment App Adoption



Average weekly purchase amounts for matched sample of 1110 customers (CBO-only, CBO-app, and Mobil Wallet). Adoption time 0 on the X-axis represents the week of app adoption, separating weeks before (on the left) and weeks after adoption (on the right). Among comparable mobile payment users, users who downloaded the app (blue- and red-dotted lines) tended to have higher purchase amounts than BAMW customers in the periods before adoption. By contrast, mobile wallet users (green line) show lower buying amounts before adopting the BAMW and subsequently had a large initial buying boost, which declines over time.

Figure 7. Causal Impact of BAMW Adoption on Purchase Amount and Frequency



DDD estimates of BAMW adoption on the natural logarithm of weekly purchase amount and frequency.

Table 1. Review of Research Quantifying the Impact of App Usage on Purchases

	Setting	Mobile payment	Physical setting	Propensity score matching	Differences-in-differences	App download vs. usage distinction	Findings
Xu et al. 2014	Add a news app to mobile news site	o	o	o	o	o	Visit incidence increases; stronger effects for consumers with high valuation for concentrated news content and with less time constraints.
Dinner et al. 2015	Add app to online and offline store	o	x	o	x	o	Purchase incidence up by app usage; more for online than offline purchase
Kim et al. 2015	App usage	o	o	x	x	o	Digital experience and browsing information from shopping apps explain purchase decisions in apps
Wang et al. 2015	Add app to website	o	o	x	x	o	Purchase frequency and low-spending customers' order size increase after adopting the app
Huang et al. 2016	Add app to website	Purchase through app or web	o	x	x	o	Purchases increase overall; slight cannibalization of website. Order size decreases after adopting the app.
Wang et al. 2018	Informational app for loyalty program	o	o	x	x	o	App adoption increases accruals. Stronger effect on occasional customers' accruals than active and accruing customers. Stronger impact on active customers' redemptions than occasional customers.
Liu et al. 2019	Add purchasing app to website	o	o	x	x	o	Purchase incidence, purchase frequency, and order size significantly increase after adopting the app
This study	Add branded-app for CBO and mobile wallet purchases to vending machine	x	x	x	x	x	Both amount per order and frequency increase with mobile wallet adoption more than with app download. High immediate impact decreases over time. Higher mobile wallet effects for recent adopters and overall app adoption effects are higher for light and medium buyers.

x = part of the study; o = not part of the study

Table 2. Characteristics of Mobile Phone Payers Before and After Launch of Branded App Mobile Wallet (BAMW)

		Nb of customers	Ln weekly amounts	SD (amounts)	Ln weekly frequency	SD (frequency)	Mean first week	Mean last week
Unmatched sample								
CBO-only	*Before launch*	9930	.653	.783	.203	.283	26.2	163
	After launch	9930	.259	.399	.078	.136	26.2	163
CBO-app	*Before launch*	1643	.742	.828	.238	.306	25.6	184
	After launch	1643	.507	.585	.161	.210	25.6	184
Mobile wallet	*Before launch*	380	.571	.767	.174	.258	26.4	191
	After launch	380	.480	.570	.151	.209	26.4	191
Matched sample								
CBO-only	*Before launch*	370	.557	.633	.168	.212	26.1	193
	After launch	370	.356	.427	.104	.137	26.1	193
CBO-app	*Before launch*	370	.593	.686	.181	.232	26.0	193
	After launch	370	.497	.523	.151	.177	26.0	193
Mobile wallet	*Before launch*	370	.572	.757	.174	.256	26.4	193
	After launch	370	.491	.573	.155	.211	26.4	193

Notes. Summary statistics of unmatched sample of 11,926 mobile phone users before covariate balancing and matching (top) and after matching (bottom). Weeks with zero purchases per customer included. Before/after launch = period before and after the week in which the branded payment app was launched (week 87). Ln weekly purchase frequency (amount) per group represents summary statistics (e.g., mean) of the individual ln purchase frequencies (amounts) (i.e., the group mean of purchase means of individuals in the group). Ln weekly amount is calculated as ln(CBO_amounts + BAMWamounts + 1) on the balanced sample containing zeros in weeks when individual did not purchase. Ln weekly frequency is amount of purchase occasions within a week, calculated as ln(CBOweekly_frequency + BAMWweekly frequency + 1). SD = standard deviation of the variable, Mean first week = average first week of purchase in the group; mean last week = average last week of purchase within the group.

Table 3. Methodological Challenges and How Our Modeling Approach Addresses Them

Methodological challenge	Explanation	Our modeling approach
1. *Self-selection* into different mobile payment instruments	Customers decide whether to download the app and adopt the mobile wallet functionality.	Use propensity score matching for three groups of customers, based on their prelaunch purchase and demographic characteristics.
2. *Nonbinary treatment* condition	In addition to the CBO-only control group, there are two app-related treatment groups (CBO-app and Mobile Wallet payers through the app).	Use matching algorithms that allow for multivalued treatment conditions with more than two matching groups. Use CBPSs to create matched triplets of customers from three groups.
3. *Endogenous selection of adoption time*	Customers endogenously decide on the timing of the adoption, so there are no unique pre- and posttreatment periods, but they differ for each customer.	Endogenous selection of the time windows for three groups based on the observations of the first and last purchase weeks.
4. *Longitudinal data structure*	We observe weeks with (or without) purchase over the observation window of 212 weeks.	Panel data estimation procedure on the matched sample, with two-way fixed effects to account for unobserved customer and time heterogeneity.

Table 4. Variable Operationalization

Variable	*Description*
Ln Purchase Amount (Y^{Am})	Natural logarithm of individual's weekly purchase amounts with CBO or/and BAMW payments [$\ln(Y^{Am}+1)$]
Ln Purchase Frequency (Y^{Fr})	Natural logarithm of individual's weekly purchases (purchase occasions) with CBO or/and BAMW payments [$\ln(Y^{Fr}+1)$]
Mobile wallet customer (I_i^{MW})	Indicator for customers who adopted BAMW payment (1, 0 otherwise)
CBO-app customer (I_i^{CBOapp})	Indicator for customers who downloaded the app but never registered for BAMW (1, 0 otherwise)
App adopters ($I_i^{CBOapp\ or\ MW}$)	Indicator for mobile wallet customer or CBP-app customer (1, 0 if CBO-only customer)
Post-adoption periods ($Post_{it}$)	Indicator for weeks before and after individual's BAMW adoption (1=weeks after adoption, 0=otherwise). For CBO customers, the indicator matched based on triplet with BAMW.
Adoption week ($Post_{it}^{AdoptWk}$)	Indicator for the week of BAMW adoption (1, 0 otherwise)
Post-adoption weeks ($Post_{it}^{AdoptWk+n}$)	Indicator for the week(s) after the week of BAMW adoption (1, 0 otherwise). $\mathrm{Post}_{\mathrm{it}}^{\mathrm{AdoptWk+1}}$= first week after the adoption week, and so on.
Early adopter ($I_i^{EarlyAdopter}$)	Indicator for customer who adopted in early periods, before week 150 (1, 0 otherwise)
Heavy spender ($I_i^{HeavySpend}$)	Indicator for a customer who had above the media spending in the pre-launch periods (1, 0 otherwise)
CBPS matching variables	
Ln weekly purchase amount before app launch/tenure	Natural logarithm of individual's average weekly purchase amounts before the app launch (< week 87) divided by the tenure
Ln weekly purchase frequency before app launch	Natural logarithm of individual's average weekly purchase frequencies before the app launch (< week 87) divided by the tenure
Tenure before the app launch	Number of weeks between the week of first joining CBO-only until the app launch week (week 87)
Month of joining CBO	The month/year in which customer first joined CBO
Geo-location based on ZIP code	Area in which the individual most frequently used the app
Last week of purchase	Recency, the week in which the last purchase observation is registered per individual

Table 5. Characteristics of Mobile Phone Payers with the Actual Time of BAMW Adoption Taken into Account (Matched Sample)

		Nb of customers	Weekly amounts	Ln Weekly amounts	Weekly frequency	Ln Weekly freq	Mean first week	Mean last week
CBO-only	*Before adoption*	370	3.88	.382	.236	.115	26.1	193
	After adoption	370	4.76	.445	.240	.124	26.1	193
CBO-app	*Before adoption*	370	5.22	.476	.315	.147	26.0	193
	After adoption	370	6.84	.557	.346	.164	26.0	193
Mobile wallet	*Before adoption*	370	3.89	.351	.246	.110	26.4	193
	After adoption	370	12.20	.880	.633	.273	26.4	193

Descriptives of purchase behavior of matched sample when actual week of branded payment app adoption is considered (rather than the general week of app launch as in Table 2). Weekly purchase frequency (amount) per group represents group average of individual average weekly purchase frequencies (amount) (i.e., the group mean of purchase means of individuals in the group). SD = standard deviation of the variable; mean first week = average first week of purchase in the group; mean last week = last observed week in which purchase occurred. Ln weekly amounts is calculated as ln(CBO_amounts + BAMWamounts + 1) on the balanced sample containing zeros in weeks when individual did not purchase. Ln weekly frequency is amount of purchase occasions within a week, calculated as ln(CBOweekly_frequency + BAMWweekly frequency + 1).

Table 6. Results of DDD Estimation

	Est.[1]	Sig.	SE[2]	% change[3] =exp(est.)-1
	Ln_Purchase Amounts			
BAMW_adoption week effect	**3.023**	***	.042	19-fold*
BAMW_week after effect	**.924**	***	.089	152%
BAMW_medium term (month)	**.761**	***	.059	114%
MW_long term (+6 weeks)	**.225**	***	.024	25%
App_adoption effects	**.059**	***	.019	6%
Postadoption weeks	.006	ns	.016	
	Ln_Purchase Frequencies			
BAMW_adoption week effect	**.935**	***	.024	155%
BAMW_week after effect	**.308**	***	.031	36%
BAMW_medium term (month)	**.252**	***	.021	29%
BAMW_long term (+6 weeks)	**.077**	***	.008	8%
App_adoption effects	**.019**	**	.006	2%
Postadoption weeks	.002	ns	.005	

Observations:180,902 on 1110 customers. Purchase amount: R^2 .0219, F(6, 179575) = 670.835, p =.000. Purchase frequency: R^2 .0205, F(6, 179575) = 624.897, p = .000.

[1] Estimates in DDD models in Eq. 1, Sig: *** p < .000; ** p < .001; * p < .05; * p < .10.

[2] Double-robust corrected standard errors (Newey–West).

[3] Percentage change relative to the baseline before mobile wallet app adoption; note that this large impact is due to adoption of the app when customers plan to use it (in the adoption week), and ln values are relatively small as they include weeks without purchase (zero purchase).

Table 7. Descriptives for Heavy versus Light Spenders and Early versus Late Adopters

		Mobile Wallet		CBO-app		CBO-only	
		Avg. weekly amount	*Avg. weekly frequency*	*Avg. weekly amount*	*Avg. weekly frequency*	*Avg. weekly amount*	*Avg. weekly frequency*
Heavy spenders (above median)	*Before adop.*	6.71	.426	7.96	.487	6.24	.382
Heavy spenders (above median)	*After adopt.*	13.1	.710	8.13	.422	6.02	.309
Light spenders (below median)	*Before adop.*	1.28	.071	2.10	.116	1.36	.079
Light spenders (below median)	*After adopt.*	8.98	.475	5.50	.277	2.44	.124
Early adopters	*Before adop.*	4.72	.304	4.52	.280	3.47	.220
Early adopters	*After adopt.*	11.0	.611	6.96	.362	3.92	.205
Late adopters	*Before adop.*	2.93	.175	5.34	.317	4.06	.241
Late adopters	*After adopt.*	10.8	.538	6.71	.335	5.06	.251

Table 8. Results of the DDD analyses with moderators

		Ln_Purchase amount				Ln_Purchase frequency			
		Est.[1]	**Sig.**	**SE[2]**	**% change[3] =exp(est.)-1**	**Est.[1]**	**Sig.**	**SE[2]**	**% change[3] =exp(est.)-1**
Early adopters equations	Average effect of app adoption (ρ_1)	**.053**	**	.020	5%	**.018**	**	.006	2%
	App adoption effect for early vs. late adopters (θ_1)	**.090**	**	.020	9%	**-.021**	***	.004	-2%
	Average effect of BAMWadoption (φ_1)	**.338**	***	.022	40%	**.113**	***	.007	12%
	BAMWadoption effect for early vs. late adopters (ω_1)	**-.087**	***	.022	-8%	**-.025**	***	.007	-2%
	Postadoption periods (δ_1)	**.049**	**	.017		**.015**	**	.005	
	Postadoption periods × early adopter (μ_1)	**-.068**	***	.013		**-.021**	***	.004	
Heavy spenders equations	Average effect of app adoption (ρ_2)	**.055**	**	.019	6%	**.018**	***	.006	2%
	App adoption effect for heavy vs. light spenders (θ_2)	**-.046**	*	.019	-4%	**-.016**	***	.006	-2%
	Average effect of BAMW adoption (φ_2)	**.314**	***	.022	37%	**.106**	***	.008	11%
	BAMW adoption effect for heavy vs. light spenders (ω_2)	.004	ns	.022		.004	ns	.008	
	Postadoption periods (δ_2)	**.047**	**	.016		**.014**	**	.005	
	Postadoption periods × heavy spender (μ_2)	**-.111**	***	.013		**-.037**	***	.004	

Observations:180,902 on 1110 customers. Purchase amount: R^2 .010, F(6, 179575) = 310.557, p = .000. Purchase frequency: R^2 .011, F(6, 179575) = 318.625, p = .000.

[1] Estimates in DDD models in Eq. 2 & 3, Sig: *** p < .000; ** p < .001; * p < .05; ‘ p < .10.

[2] Double-robust corrected standard errors (Newey–West).

[3] Percentage change relative to the baselines before mobile wallet app adoption.

Table 9. Model-Free Evidence of Purchases in CBO and BAMW Channels in the Postlaunch period

		Ln total weekly amounts (CBO+MW)	Ln CBO weekly amounts	Ln BAMWweekly amounts
Mobile wallet payers	CBO payments only	3.27	3.27	0
	App_only	3.25	0	3.25
	Multichannel	4.03	3.21	3.33
CBO-app	CBO payments only	3.38	3.38	0
CBO-only	CBO payments only	3.22	3.22	0

Table 10. Separate DDD Analyses for CBO Purchases Only

	CBO purchase amounts only		
	Est.[1]	Sig.	SE[2]
Ln BAMW amount	-.054	***	.012
BAMW adoption week effect	.654	***	.083
BAMW_week after effect	.218	***	.064
BAMW_medium term (1st month)	.221	***	.046
BAMW_long term (+6 weeks)	.029	ns	.022
App_adoption effects	.065	**	.020
Postadoption periods	-.029	ns	.017
	CBO purchase frequency only		
lnBAMW_frequency	-.064	***	.013
BAMW_adoption week effect	.208	***	.028
BAMW_week after effect	.078	***	.022
BAMW_medium term (1st month)	.077	***	.016
BAMW_long term (+6 weeks)	.015	*	.007
App_adoption effects	.021	**	.007
Postadoption periods	-.010	ns	.005

[1] Effects of BAMW adoption on CBO purchases only; 171,567 observations on 1110 customers. Amounts equation: $F(7, 170239) = 29.2509$, $p = .000$; $R^2 = .001$. Frequency equation: $F(7, 170239) = 33.39$, $p = .000$; $R^2 = .001$. CBO purchase amounts only = $\ln(\text{CBO amounts}_{it} +1)$, aggregate individual weekly spend via CBO payment instrument; CBO purchase frequency = $\ln(\text{CBO frequency}_{it}+1)$, individual weekly purchase frequency/occurrence of purchase; lnBAMW amount = $\ln(\text{BAMW amount}_{it} +1)$, aggregate individual weekly spending with BAMW payment instrument; specification equivalent to Eq. 1. Sig: *** $p < .000$; ** $p < .001$; * $p < .05$; ‘ $p < .10$. [2] Double-robust corrected standard errors (Newey–West);

Table 11. Robustness Check Specification

		Unmatched sample			Matched sample (rob. check)		
		N	**Ln weekly amounts**	**Ln weekly frequency**	**N**	**Ln weekly amounts**	**Ln weekly frequency**
CBO-only	*Before launch*	9930	.653	.203	298	.631	.198
	After launch	9930	.259	.078	298	.410	.122
CBO-app	*Before launch*	1643	.742	.238	298	.533	.161
	After launch	1643	.507	.161	298	.527	.162
Mobile wallet	*Before launch*	380	.571	.174	298	.442	.135
	After launch	380	.480	.151	298	.454	.142

Notes. Summary statistics of unmatched sample of 11,926 mobile phone users before robustness check matching and 298 triplets after matching (see Section 7). Weeks with zero purchases per customer included. Before/after launch = period before and after the week in which the branded payment app was launched (week 87). Ln weekly purchase frequency (amount) per group represent summary statistics (e.g., mean) of the individual ln purchase frequencies (amount) (i.e., the group mean of purchase means of individuals in the group).

Table 12. Robustness Check Estimation Results of DDD Models

	Est.[1]	Sig.	SE[2]	% change[3] =exp(est.)-1
	Ln_Purchase Amounts			
BAMW_adoption week effect	**3.002**	***	.050	19-fold*
BAMW_week after effect	**.845**	***	.103	133%
BAMW_medium term (month)	**.556**	***	.059	74%
BAMW_long term (+6 weeks)	**.168**	***	.027	18%
App_adoption effects	**.085**	***	.025	9%
Postadoption periods	**-.046**	*	**.021**	
	Ln_Purchase Frequencies			
MW_adoption week effect	**.905**	***	.028	147%
MW_week after effect	**.281**	***	.036	32%
MW_medium term (1st month)	**.180**	***	.021	20%
MW_long term (+6 weeks)	**.055**	***	.009	6%
App_adoption effects	**.032**	**	.008	3%
Postadoption periods	**-.015**	*	**0.007**	

Observations: 124,648 on 801 customers. Purchase Amount: R^2 .019, F(6, 123631) = 402.927, p = .000. Purchase frequency: R^2 .017, F(6, 123631) = 354.504, p =.000.

[1] Estimates in DDD models in Eq. 1, Sig: *** p < .000; ** p < .001; * p < .05; * p < .10.

[2] Double-robust corrected standard errors (Newey–West).

[3] Percentage change relative to the baseline before mobile wallet app adoption; note that this large impact is due to adoption of the app when customers plan to use it (in the adoption week), and ln values are relatively small as they include weeks without purchase (zero purchase).

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Appendix:
Procedure Description of Observation Study and Experimental Design

For the observational study, we focused on university students, as the data provider identified them as the main target audience for the introduction of mobile payments. Within one regular day at the beginning of December 2018, six groups of research assistants (two per group) observed 124 purchases at different vending machines and coffee shops at a Norwegian university. At these places, buyers can purchase with phone or credit card (in this society, cash transactions are rather rare, with only 5.6% of all observed transactions cash transactions). In total, 13.7% of transactions were phone payments, and remaining 80.7% were bank card payments. After buying and paying for their products, buyers were approached by the research assistants and asked to respond to our survey. Respondents were asked about their satisfaction with items bought, payment process, and payment experience and their perceptions of a series of statements related to payment options.

Experimental Design to Test the Pain of Paying between Mobile and Bank Card Payments

We conducted the experiment at the same Norwegian university, with a sample size of 240. The procedure was as follows: upon entering the experimental lab, respondents were directed to separate rooms with computers. After consenting to the study, the respondents were randomly assigned to one of the four priming scenarios (priming the use of phone versus card × priming the type of use: neutral, for personal purposes or for social purposes):

Priming tasks descriptions
Use of Phone:

> Please take a moment to think about situations in which you use your mobile phone for **personal/social reasons**. Really visualize when and how you use your mobile phone for **personal/social reasons**.
> In the space provided below, please describe at least 5 such situations in which you use your mobile phone for **personal/social reasons**.

Neutral phone condition: Please take a moment to think about situations in which you use your mobile phone. Really visualize when and how you use your mobile phone. In the space provided below, please describe at least 5 such situations in which you use your mobile phone.

Use of Bank Card:

> Please take a moment to think about situations in which you use your bank card (for personal/social reasons). Really visualize when and how you use your bank card (for personal/social reasons).
> In the space provided below, please describe at least 5 such situations in which you use your bank card (for personal/social reasons).

After completing the priming tasks, respondents were presented with the following scenario:

> Please imagine that you are at school on a regular day. During one of the course breaks, both you and a close friend decide to grab a bottle of Coca-Cola at the vending machine in the refreshment area. When you guys get to the refreshment area you approach the vending machine together, as you both wish to purchase a drink. There is no queue. You approach the vending machine before your friend. You get your **mobile phone/bank card** out to make a payment to grab a bottle of Coca-Cola.

We used Coca-Cola as an example of a product this group can easily relate to in the scenarios.

Next, on the scale from 1 (completely disagree) to 9 (completely agree), respondents were asked the following:

1. *It was painful to think about paying for my friend's Coca-Cola.*
2. *It was fun thinking about treating my friend to a Coca-Cola.*
3. *It was convenient thinking about paying for my friend's Coca-Cola.*
4. *I felt good thinking about paying for my friend's Coca-Cola.*
5. Likelihood of paying for the products was accessed on a scale from 1 (not at all likely) to 9 (extremely likely), using the question: *How likely are you to pay for your friend's Coca-Cola as well as your own using your mobile phone to make the payment?*

Next, we asked all respondents a series of questions about their perceptions of payment convenience, novelty, fun, speed, and easiness and security when paying with mobile phones versus bank cards. We also asked several control questions such as frequency of use of vending machines and purchase habits in the soft drink category.