Essays in Empirical Finance

Doctoral Thesis

submitted to

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Gießen, 29th of January 2021

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2 The 24/7 anywhere branch: Mobile-banking improves financial decision-making – or does it?

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Working Paper, January 2021

Own Share: 60%

Abstract

Mobile-banking – making banking transactions through mobile devices like smart phones – might improve financial decision-making by customers. Our study finds customers to retrieve information about their financial situation more often after adopting mobile-banking. In addition, we document that the higher transparency about the financial situation is associated with improved financial decision-making of mobile-banking users. Concretely, we find mobile-banking adopters to suffer less from high-interest overdraft debt. Additionally, mobile-banking adopters reduce overdraft interest and fees by reducing consumption spending, increase credit card utilization and transfer liquidity from savings accounts in times of overdraft. Finally, we show that those mobile-banking adopters, who formerly did not use the online banking service of the bank, benefit from mobile-banking adoption the strongest.

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2.1 Introduction

In this paper we examine whether clients are able to increase financial attention after mobile-banking adoption and how they, by this, are able to improve financial decision-making capabilities. Mobile-banking evolves to the state of the art channel for daily banking activities. In 2018 finance apps have been downloaded 3.4bn times globally, which documents a massive increase by +75% compared to 2016. While Asia Pacific can be referred to as the global leader with respect to mobile-banking activities, North America and Europe are the second strongest areas. In those regions, finance app downloads doubled from 200 mio. in 2012 to 400 mio. in 2018 (Haslam, 2019; Liftoff and Leanplum, 2019). The value of the global mobile banking market is estimated at $715.3 million in 2018 and expected to surge to $1.82 billion in 2026, representing a CAGR of 12.2% from 2019 to 2026 (Allied Market Research, 2020). By enabling instant, on the go connections across all stages of the customer journey, these disruptive forces offer the potential to change customers banking activities fundamentally. But offers mobile-banking real value to its users? Does mobile-banking adoption unlock the opportunity for an optimization of customers financial management? Or are private households unable to benefit from these instant connections to their bank?

Recent empirical work concerning mobile app adoption in different industries outlines increased attention and various changes in customers behavior after adoption. For example, patients are able to increase healthy daily movement (Bond et al., 2014; McCallum et al., 2018), reduce unhealthily high blood pressure (Liu et al., 2013) or improve their home-based rehabilitation efforts after hospitalization or the start of new medications (Dobkin and Dorsch, 2011).[1] With respect to financial decision-making, Levi and Benartzi (2020) and Carlin et al. (2019) investigate fintech users, who start to use the mobile app, and document more frequent logins, increased credit card utilization and reduced overdraft fees as well as a decline in discretionary consumption spending. However, these studies focus a specific target group that self-selected to some extent into a prior service, e.g. a fintech. Due to our knowledge, we are the first who examine how customers change their financial decision making after adopting mobile-banking, which is provided from the main bank to all of their clients and not from a third party to a specific target group. By this, we are able to derive holistic insights on how the adoption of the banks offered mobile-banking service is associated with changes in clients financial behavior.

We receive large scale individual level panel data from a German bank. These data covers 109,268 private customers, who are observed on a daily basis for a 22-month period from January 2017 to October 2018. We start our analysis by investigating on whether mobile-banking adoption is associated with increased financial attention. We show that the probability of a daily account inquiry increases by 112%

1 Studies linking mobile apps and physical health typically investigate clients using wearables, e.g. a smart watch or an armband, which measures the current health situation. This wearable transfers the data to the mobile app, where results get presented and the user interaction takes place.

relative to the sample mean after mobile-banking adoption. Such an increase in awareness should be associated with improved financial decision-making, e.g. stronger capabilities to reduce costly checking account overdraft (Jørring, 2020; Stango and Zinman, 2014). We find that the probability of facing at least one day with overdraft in a particular month decreases by -9.26% relative to the sample mean after mobile-banking adoption. Thus, mobile-banking supports customers to completely avoid costly overdraft. In addition, clients improve their financial decision-making in times of overdraft after adopting mobile-banking. We examine three liquidity preserving strategies, namely reduction in consumption spending, increased credit card utilization and transfers from savings accounts, that prevent additional overdraft fees. We find improvements in every strategy after mobile-banking adoption. Concretely, after adopting mobile-banking clients reduce their consumption spending in times of overdraft by additional -7.89 percentage points. This represents an improvement of +74% compared to those times prior mobile-banking adoption. Furthermore, after mobile-banking adoption credit card utilization, which provide a liquidity effect to the client, rises in times of overdraft by additional 1.93 percentage points. This corresponds to an increase of 244% in this liquidity preserving strategy compared to those times prior mobile-banking adoption. With respect to transers from savings accounts, we document mixed results. Even though we do not find a general change in transferring behavior after mobile-banking adoption, we examine that a mobile-banking account inquiry at a day with overdraft is associated with a 12% increase in transfers from savings accounts. Thus, active mobile-banking usage is also associated with improvements in this liquidity preserving strategy. Finally, we show that our findings regarding the positive effect of mobile-banking adoption on account inquiries, reductions in consumption spending as well as improved credit card utilization during times of overdraft are the strongest for those customers, who formerly did not use the online-banking service of the bank.

These results contribute to the literature in several ways. First, we add up to research on mobile-banking. Prior studies are mostly survey based and analyze factors affecting the adoption of mobile-banking (Cope et al., 2013; Koenig-Lewis et al., 2010; Laukkanen and Pasanen, 2008; Laukkanen and Cruz, 2012; Luo et al., 2010; Saeed, 2011). Becker et al. (2020) enlarge this body of survey-based literature by analyzing transaction data in order to examine drivers of mobile-banking adoption. Furthermore, they find changes in clients channel usage, payment behavior and business intensity with the bank. Our paper adds to this literature by investigating changes in customers financial decision-making after mobile-banking adoption, which represents, most recently, the fastest growing banking channel in financial service industry.

Second, our study is also related to fintech-based analyses. Levi and Benartzi (2020) as well as Carlin et al. (2019) investigate changes in financial behavior by analyzing transaction data of fintech users, who start to use the related mobile app. But, only a fraction of most recent society already uses digital banking channels. For example, in 2017 37% (43%) of the US (German) citizens, respectively, do not use online-banking at all and around 45% state that branches and ATMs are the primary method to access their bank accounts (Federal Deposit Insurance Corporation, 2017; Statistisches Bundesamt, 2018). Thus, customers who use digital banking channels represent a fraction of the overall society and fintech based studies analyze those customers, who already self-selected into the digital service. Due to the best of our knowledge, our study is the first that utilizes omni-channel transaction data from a bank, which offers mobile-banking to all of its clients, to examine aggregate effects of mobile-banking adoption. By doing this, we cover a cross section of the society and show that prior studies, which examine the association of fintechs mobile app adoption with financial transparency, changes in consumption spending as well as credit card utilization, potentially underestimate aggregate effects of mobile-banking adoption.

Third, we add to studies examining clients utilization of checking account overdraft. This sort of debt, especially their fees and interest rates, are controversial and heavily discussed. In 2015, low-income U.S. households spent USD 24bn on checking account overdraft fees (Schmall and Wolkowitz, 2016). With respect to these checking account overdrafts, politicians, regulators and consumer protectors blame e.g. the high discrepancy between base rates and overdraft interest rates, hidden fees and too little transparency about appropriate and less costly credit products. Customers demand for overdraft differentiates into two categories: 'financial conditions' and 'imperfect decisions' (Carvalho et al., 2019). While high-interest debt seems to be the only source for additional liquidity in situations of the first category 'financial conditions', the second category 'imperfect decisions' refers to financial mistakes of the client. Several studies document that 'imperfect decisions', which are also of main interest of our study, are a major driver of overdraft or similar payday loan utilization (Agarwal et al., 2009; Alan et al., 2018; Carvalho et al., 2019; Jørring, 2020; Stango and Zinman, 2009). In this context financial attention seems to be a relevant dimension in reducing overdraft utilization (Carlin et al., 2019; Stango and Zinman, 2014). However, very little is known on how the adoption of the banks offered mobile-banking service, which is potentially linked to increased financial attention, is associated with overdraft utilization. Our results fill this gap by showing that clients improve capabilities to completely avoid overdraft after mobile-banking adoption. Furthermore, we document that mobile-banking adopters stronger prevent additional overdraft by reducing consumption spending, increasing credit card utilization and transferring money from low-interest saving accounts in times of overdraft. Thus, mobile-banking turns out to be more than just a trendy gadget and comes up as an auxiliary instrument in reducing controversially discussed high-interest overdraft debt.

Eventually, we perform two further investigations to complement these main analyses. First, we show that our results on account inquiry behavior are more consistent with rational inattention, where clients try to e.g. prevent financial distress and avoidable fees (Nieuwerburgh and Veldkamp, 2009; Reis, 2006; Moscarini, 2004; Sims, 2003), instead of selective attention models, where clients generate higher utility from receiving good news instead of bad news, e.g. about future consumption capabilities (Koszegi and Rabin, 2009; Karlsson et al., 2009; Galai, 2006). By this, we add to an ongoing academic discussion about drivers of financial attention. While Sicherman et al. (2016) investigate selective attention of retail investors to portfolio information, our study documents that customers tend to act rational instead of selective when it comes to account inquiries. This finding stands in contrast to Olafsson and Pagel (2019). Second, theoretical frameworks assume that ease of use strongly impacts self-service channel adoption and usage in retail banking (Davis and Davis, 1989; Rogers, 2003; Venkatesh et al., 2003). We include information about the method that a client uses to authenticate overdraft balancing transfers. We find that the easier a client can authenticate the desired transfer the more frequently a client makes use out of this balancing potential. Due to our knowledge, we are the first, who incorporate transaction level data from a bank to observe an association of ease of use with channel utilization. By this, we document results supporting those theoretical frameworks.

The remainder of the paper proceeds as follows. Section 2.2 characterizes both the retail banking and overdraft market in Germany. We outline characteristics of our data in section 2.3. Section 2.4 investigates associations of mobile-banking adoption with clients account inquiry behavior, which we use to measure financial attention of the customer. Section 2.5 examines how overdraft consumption changes after mobile-banking adoption. Section 2.6 provides further analyses. We discuss the results and conclude the paper in section 2.7.

2.2 Institutional Setting

The German retail banking market can be characterized as a highly developed polypoly. There exist three important groups, which build the 'three-pillar-banking-system'. These pillars differ considerably in terms of their structure. Pillar one is made up of private credit institutions, both according to their legal forms as well as their ownership structures. In terms of total assets, pillar one makes up about 40 percent of the entire German banking system. Pillar two is denoted as the savings banks group. In terms of aggregate total assets, the entire savings banks group is about as large as the group of the private credit institutions. Pillar three is made up by the cooperative banking group. It comprises a larger number of independent institutions than the other two groups, whereas in terms of total assets it is only about half the size of the two other pillars (Behr and Schmidt, 2015).

Germany can be denoted as a bank-based financial system, in which banks mostly establish long-lasting relationships with their customers. Within each pillar, banks are frequently organized in groups, by which they are able to offer a broad range of financial services like deposits, payment transaction, loans, insurance or investment funds (Behr and Schmidt, 2015; Schmidt and Tyrell, 2004). Most clients receive their financial services from one bank, the main bank or so called "house bank". By analyzing transaction data of a German bank, researches receive a quite holistic view on the financial behavior of the observed customers.

Dimension	2015	2018	Percentage Change
Population & Financial Institutions			
Population (thousands)	81,687	82,902	+1.5%
Number of financial institutions	1,774	1,584	-10.7%
thereof private credit institutions	276	263	-4.7%
thereof savings banks	425	399	-6.1%
thereof cooperative banks	1,049	917	-12.6%
thereof others	24	5	-79.2%
Number of local bank branches	34,115	27,993	-17.9%
Number of ATMs	86,702	85,885	-0.9%
Digitization of Households			
Share of households with a PC	87%	90%	+3.4%
Share of households with a mobile phone	94%	97%	+3.2%
Share of households with internet access	79%	93%	+17.7%
Share of households using online-banking	52%	59%	+13.5%
Checking Account Overdraft			
Revolving Volume (millions)	35,038	31,488	-10.1%
Effective Interest Rate (p.a.)	9.03%	8.26%	-8.5%
Debit and Credit Cards			
Cards with a debit function (thousands)	106,103	110,934	+4.6%
Cards with a delayed debit function (thousands)	28,245	30,213	+7.0%
Cards with a credit function (thousands)	4,900	5,678	+15.9%

Table A-1: Key dimensions characterizing the German retail banking market. Column 2 documents values out of year 2015, column 3 values out of year 2018 and column 4 shows the percentage change from 2015 to 2018. Row 4 and 5 sum up values of the savings and cooperative banks as well as their related institutions like *Landesbanken*. The values for households with internet access also include mobile internet access (smartphone, surf sticks etc.). The values characterizing the market for checking account overdraft present the average of the corresponding end-of-months value in that particular year. The values in column 2 and 3 are obtained from Deutsche Bundesbank (2020a,b, 2019a); Statistisches Bundesamt (2019b) and Statistisches Bundesamt (2015).

Compared to global peer markets, long-term profitability is low and German banks struggle to earn their cost of capital. Major reasons for this situation are the highly competitive market, a strong dependency on net interest income with comparative low prices for banking products and services in combination with a rigid cost base, driven by high branch density and a large staff base (Koch et al., 2016).

Table A-1 documents some key figures, which characterize the German banking system. As the overall population grew from 2015 to 2018 by +1.5%, the number of banks diminished by -10.7%, which seems to be one result of the highly competitive situation in the German banking system. Even though consolidation takes place, the market is still fragmented with more than 1,500 banks competing for the customers.

Moreover, Table A-1 outlines that German citizens are prepared to behave increasingly digital. In 2018 almost every household possesses a mobile phone (97%) and most of them a personal computer (PC) (90%). Furthermore, the number of households with internet access (online-banking) increased by +17.7% (+13.5%) to 93% (59%) from 2015 to 2018, respectively. At the same time banks diminished their local branch network by -17.9% to account for changes in customer demand as well as price pressure in the market. These values show up a highly dynamic banking system, which is among others strongly influenced by digitization. Koch et al. (2016) outline the low-interest-rate environment, regulatory tightening and digitization as the most relevant environmental factors for German banks and denote the digitization strategy as an key enabler for them to improve the cost base as well as to extend revenue pools.

Besides a strong and recent digitization of the German financial services industry, Germany is also suitable for an investigation of customers overdraft behavior. German households reduced the end-of-month revolving overdraft volume from 35.0bn in 2015 to 31.5bn in 2018 and, thus, by -10.1%. Even though the average effective interest rate of such debt decreased by -8.5% at the same time, German households still have to pay costly 8.26% p.a. interest on checking account overdraft. One can observe several attempts of consumer protectors, regulators and politicians that aim to reduce overdraft consumption of the German society. For example, German consumer protectors frequently publish and claim overdraft fees of German banks (Stiftung Warentest, 2020). Like in the US, German regulators mainly focus on enforcing banks to provide sufficient transparency about overdraft and related credit products. Similar to the *Overdraft Payment Supervisory Guidance* in the US, the *Mortgage Credit Directive* and *Payment Service Directive* in Europe/Germany force banks, among others, to ensure that customers are able to choose the credit product most suitable for their financial needs, provide comprehensible overview about overdraft fees, monitor accounts constantly and offer alternatives, if a customer uses overdraft too frequently (Federal Deposit Insurance Corporation, 2010, 2015; Bundesamt für Justiz, 2016, §504). By now, whether in the US nor in Germany, fees or interest rates of overdraft are strictly limited. Even if German politicians discuss strict limitations occasionally (Deutscher Bundestag, 2018; Drost, 2019; Lay, 2014), so far only general regulations regarding *unfair or deceptive acts or practices* are applicable to overdraft fees in the US as well as in Germany (Federal Deposit Insurance Corporation, 2015; Federal Trade Commission, 2016; Bundesanstalt für Finanzdienstleistungsaufsicht, 2019; Bundesamt für Justiz, 2016, §138).

The utilization of credit cards is one instrument to avoid overdraft. Customers could use credit cards in order to make use out of the liquidity effect, which results out of the delayed debit. Cards with a direct debit function are most popular in Germany. German banks issued roughly 110.9 thousand cards with a direct debit function up to the end of 2018, which corresponds to an increase of +4.6% compared to 2015. However, cards with a delayed debit or credit function, which are both denoted as credit cards in Germany, are less popular, but expanding even stronger. German banks issued 30.2 (5.7) thousand cards with a delayed debit (credit) function up to the end of 2018, which corresponds to an increase of +7.0% (+15.9%) compared to 2015, respectively. Even though most credit cards in Germany are not linked to a credit function, they still offer a delayed debit which results in a positive liquidity effect for the client that can be used to prevent costly overdraft.

Eventually, Germany comes up as a promising area for our research regarding mobile-banking adoption and resulting changes in client's overdraft behavior. As we can observe an increase in digital behavior of German households corresponded by a rise in the number of credit cards while noticing a decrease in overdraft utilization, we can analyze a potential association of those dimensions quite reasonably.

2.3 Data

We analyze large scale individual-level panel data from a German cooperative bank. This bank is locally owned and, similar to other savings and cooperative banks in Germany, tends to attract traditional bank customers with a preference for a strong and long-lasting relationship with their house bank. Our bank offers a wide range of financial services, such as current accounts, deposit accounts, securities accounts and loans (including mortgages), to its retail customers. The bank serves over 250,000 individual customers. Those customers can use the bank's branch and ATM network, call center, online- and mobile-banking to proceed their banking activities. The bank operates over 50 branches and more than 100 ATMs, with at least one branch and ATM in every district of the operating area. The call center is available from Monday to Friday from 7 a.m. to 8 p.m. ATMs, online- and mobile banking are accessible 24 hours on 7 days a week.

Every channel supplies the customer at least with his or her actual financial status, a history of all transactions during the last 42 days and, up to ATMs, the possibility to generate bank transfers or transactions at the capital market. Figure A-1 shows the mobile- and Figure A-2 the online-banking interface, which can be seen after login. On both, balances of all accounts are visible directly, overdrafted accounts are marked in red. The banks mobile-banking app is available for iOS and Android. On ATMs customers can either print their account statements or examine the account balance on the screen. We received data for a 22-month period from January 2017 to October 2018. The anonymized data provides information about demographic characteristics, account balances, payment transactions and channel usage of the customers. Most data is on a daily basis. We focus on adult private customers with complete transaction data, at least one current account, monthly salary inflows as well as one or more account inquiries per month. We exclude employees of the bank. Eventually, we proceed with a final sample of 109,268 unique customers and 59,299,920 corresponding daily observations.

Table A-2 provides summary statistics. A definition of all variables is provided in Table A-10 in Appendix 2.9.1. As we investigate a potential association of mobile-banking adoption with overdraft behavior, we present summary statistics for our full-sample as well as subgroups of mobile-banking adopters and overdraft-users. Column *Mobile-Banking Adopters* covers all daily observations of those customers, who adopt mobile-banking during our observation period, after their adoption.[2] Column *Customers with*

2 Column *Mobile-Banking Adopters* provides descriptive statistics for those customers, who adopt mobile-banking during our observation period. Thus, we can observe characteristics of customers in this subgroup compared to those clients, who do not adopt mobile-banking during our research period. However, our full sample also includes customers, who

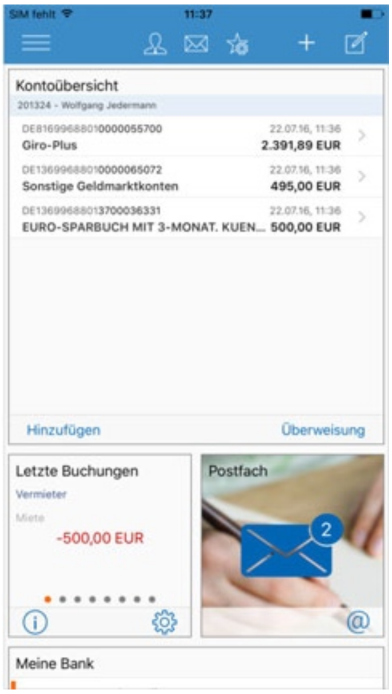

Figure A-1: Screenshot of the mobile-banking app after login. Account balances are visualized at the top, last transactions at the bottom left and the number of digital account statements at the bottom right.

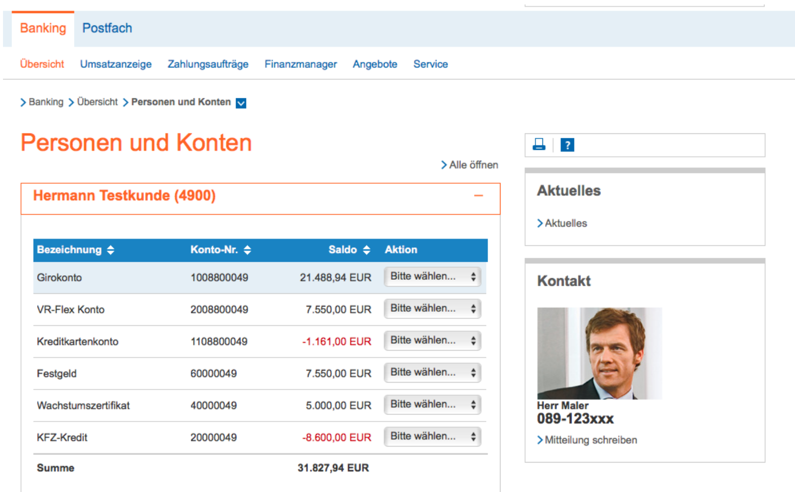

Figure A-2: Screenshot of the online-banking after login. Navigation is shown at the top, account balances at the left and the picture as well as contact information of the financial advisor at the right.

Overdraft contains all daily records of clients with overdrafted current accounts during that particular day. The three groups comprise 59.3, 2.4 and 9.3 mio. observations of 109,268, 7,990 and 60,474 distinct individuals, respectively. We calculate mobile-banking and online-banking adoption dummies which equal 0 (1) before (after) first channel usage. The full sample statistics illustrate that 19.58% of our records observe a customer after mobile-banking adoption. 18.92% of our full sample, and thus almost every mobile-banking user, utilizes both mobile- and online-banking.

adopt mobile-banking prior to our observation period, as these clients also act as controls in our later difference-in-differences estimation procedure (Goodman-Bacon, 2019).

Statistic	Full Sample Mean	Full Sample Median	Full Sample SD	Mobile-Banking Adopters Mean	Mobile-Banking Adopters Mean-Diff	Customers with Overdraft Mean	Customers with Overdraft Mean-Diff
Channel Usage							
Mobile-Adoption (IV)	0.1958	0.0000	0.3968	1.00	0.8042***	0.2700	0.0742***
Online-Adoption (IV)	0.5029	1.00	0.5000	0.8433	0.3404***	0.5762	0.0733***
Mobile- and Online-Adoption (IV)	0.1892	0.0000	0.3917	0.8433	0.6541***	0.2629	0.0737***
Inquiry Any (IV)	0.1753	0.0000	0.3802	0.3514	0.1761***	0.2175	0.0423***
Inquiry Mobile (IV)	0.0593	0.0000	0.2362	0.2836	0.2243***	0.0864	0.0271***
Inquiry Online (IV)	0.0538	0.0000	0.2257	0.0641	0.0102***	0.0631	0.0093***
Inquiry ATM (IV)	0.0695	0.0000	0.2544	0.0310	−0.0386***	0.0798	0.0102***
Indicator Variables							
Overdraft (IV)	0.1570	0.0000	0.3638	0.1740	0.0170***	1.00	0.8430***
Salary Inflow (IV)	0.0403	0.0000	0.1967	0.0397	−0.0006***	0.0170	−0.0233***
Money Inflow (ex Salary) (IV)	0.0709	0.0000	0.2567	0.0789	0.0080***	0.0672	−0.0038***
Money Outflow (IV)	0.3485	0.0000	0.4765	0.4058	0.0572***	0.3813	0.0328***
Credit Card available (IV)	0.2007	0.0000	0.4005	0.2419	0.0412***	0.2263	0.0256***
Credit Card Settlement (IV)	0.0059	0.0000	0.0764	0.0080	0.0021***	0.0078	0.0020***
Credit Card Payment (IV)	0.0211	0.0000	0.1438	0.0304	0.0093***	0.0308	0.0096***
Savings available (IV)	0.5611	1.00	0.4963	0.5399	−0.0212***	0.4924	−0.0687***
Euro Variables							
Salary Inflow (Euro)	60.00	0.0000	464.72	62.17	2.17***	19.68	−40.31***
Money Inflow (ex Salary) (Euro)	53.72	0.0000	1,958.04	54.71	0.9961	24.99	−28.73***
Money Outflow (Euro)	-111.90	0.0000	1,909.32	-111.58	0.3133	-96.40	15.50***
Credit Card Limit (Euro)	838.34	0.0000	2,137.06	880.95	42.60***	868.98	30.64***
Credit Card Settlement (Euro)	2.17	0.0000	52.12	3.02	0.8505***	3.65	1.48***
Credit Card Payment (Euro)	-2.19	0.0000	35.89	-3.13	−0.9377***	-2.98	−0.7913***
Salary Month (Euro)	1,831.66	1,604.38	2,039.29	1,854.83	23.17***	1,898.41	66.75***
Current Account Balance (Euro)	4,481.68	1,112.69	22,110.69	3,095.25	−1,386.42***	-1,035.58	−5,517.25***
Savings Accounts Balance (Euro)	10,101.16	81.78	39,561.97	5,491.96	−4,609.20***	2,569.27	−7,531.89***
Investments (Euro)	6,926.15	0.0000	43,627.41	3,487.16	−3,439.00***	1,920.62	−5,005.54***
Loans (Euro)	5,422.25	0.0000	40,958.24	4,846.57	−575.68***	10,317.72	4,895.46***
Conditional Values							
Money Inflows (ex Salary) (Euro)	805.23	194.00	7,540.99	703.02	−102.21***	377.22	−428.01***
Money Outflows (Euro)	-321.06	-94.00	3,223.79	-274.99	46.07***	-252.79	68.27***
Credit Card Limit (Euro)	4,177.15	3,000.00	2,968.01	3,641.19	−535.95***	3,840.45	−336.70***
Credit Card Payment (IV)	0.1012	0.0000	0.3016	0.1191	0.0179***	0.1317	0.0305***
Credit Card Payment (Euro)	-103.69	-49.51	224.60	-102.77	0.9271	-96.94	6.76***
Demographics							
Age (Years)	51.49	51.33	19.53	35.79	−15.70***	47.69	−3.80***
Male (IV)	0.4862	0.0000	0.4998	0.5368	0.0506***	0.5189	0.0327***
N	59,299,920			2,372,032		9,311,205	
Individuals	109,268			7,990		60,474	

Table A-2: Descriptive statistics of our data on a daily basis. A definition of all variables is provided in Table A-10 in Appendix 2.9.1. Column *Full Sample* present sample means of the full sample. Column *Mobile-Banking Adopters* covers all daily observations of those customers, who adopt mobile-banking during our observation period, after their adoption. Column *Customers with Overdraft* contains all daily records of clients with overdrafted current accounts during that particular day. Column *Full Sample* provides mean, median and standard deviation of the variables. The columns *Mobile-Banking Adopters* and *Customers with Overdraft* document mean values of the variables as well as mean-differences in % compared to the full sample. Almost all mean-differences are significant at a 0.01%-level, which we check by a two-sided t-test.

We observe a probability of an account inquiry through any channel of 17.53% per day. Regarding different channels, we investigate probabilities of 5.93% for a mobile-banking, 5.38% for an online-banking and 6.95% for an ATM inquiry. With respect to the subgroup of mobile-banking adopters, we observe more frequent account inquiries. The probability of an inquiry through any channel increases to 35.14%, mobile- and online-banking inquiries are more usual while those via ATM's are more seldom compared to the full sample. We will examine a potential association of mobile-banking adoption with login frequency in section 2.4 in more detail. The mean values of account inquiries in the subgroup of overdraft-users are likewise higher than the full-sample means. Therefore, customers, who face an overdrafted current account, seem to check their accounts more frequently. These univariate indications will also be investigated in section 2.4, 2.5 and 2.6 by multivariate analyses.

Moreover, almost every sixth time point (15.7%) represents an observation with an overdrafted current account and therefore a customer, who is confronted with highly expensive unsecured debt. Money outflows take place with a likelihood of 34.85% and therefore every third day. 20.07% of all observations possess a credit card. In the full sample payments by these cards happen on 2.11%, credit card settlements on 0.59% of all days. Conditional on possessing a credit card with available spending limit, a customer pays with a probability of 10.13% by credit card and, conditional on observing a day with a credit card payment, the daily credit card spending sums up to 104€ on average.

The average customer is 51 years old, receives a monthly salary of 1,832€, holds 4,482€ in current-, 10,101€ in savings-, 6,926€ in investment-accounts and 5,422€ in bank loans on average. The fact that 49.24% of all customers with overdraft hold liquid savings, which could be used instantly to (at least partially) settle overdraft, is of special interest. This subgroup faces and end-of-day overdraft of -1,036€ while holding 2,569€ end-of-day in savings accounts on average. We will analyze these possible settlements explicitly in section 2.5.2.

Table A-3 compares selected dimensions of our full sample with the overall German society. The mean values of our sample are mostly similar to overall German statistics. As we focus on adult customers in our study, clients in our sample are slightly older than the German average. Furthermore, our clients are somewhat more wealthy than the German average. Taken as a whole, we are able to analyze a representative sample of the overall German society. As our research site offers their services to a broad range of clients, we are confident to examine data which is selected almost randomly with minor self-selection issues.

Finally, we have to notice that our data provides information about daily money in- and outflows, but these transactions are uncategorized. In order to approximate categorized spending in general as well as consumption spending in particular, we receive monthly aggregated data about payment categories for each individual. Based on these data, we are able to approximate consumption spending as described in

Statistic	Mean Full Sample	Statistics Germany
Age (Years)	51.49	44
Male (IV)	0.4862	49
Mobile-Adoption (IV)	0.1958	22%
Online-Adoption (IV)	0.5029	59%
credit card available (IV)	0.2007	36%
Savings available (IV)	0.5611	60%
Salary Month (Euro)	1,831.66	1,570
Current Account Balance (Euro)	4,481.68	3,622
Savings Accounts Balance (Euro)	10,101.16	4,539
Investments (Euro)	6,926.15	4,539
Loans (Euro)	5,422.25	8,621

Table A-3: Comparison of selected dimensions of our full sample with overall German statistics. Full sample values are described in Table A-2 in more detail. German statistics on Age, Gender, Online-Adoption and Salary are extracted from Statistisches Bundesamt (2019a), statistics on Mobile-Adoption and available savings are extracted from Gesellschaft für integrierte Kommunikationsforschung (2019), statistics on Account Balances are extracted from Deutsche Bundesbank (2019b) and statistics on available credit cards are extracted from Deutsche Bundesbank (2018).

Appendix 2.9.2. Furthermore, our further analysis documented in section 2.6.2 investigates a potential association of ease of use of mobile-banking usage and clients overdraft balancing behavior. In order to measure ease of use of money transfers initiated by mobile-banking, we receive data about the method by which the customer generates the second factor to authenticate the transfer, which is required for regulatory reasons. These data, by which we are able to observe ease of use of a banking channel, is described in section 2.6.2 in more detail.

2.4 Mobile-Banking Adoption and Financial Transparency

Consumers face limited capacity for obtaining and proceeding information. Hence, they have to trade off (opportunity) costs of obtaining information with the expected benefits (Moscarini, 2004; Sims, 2003). Customers receive information about their current financial situation e.g. by inquiring their actual account balances. Banking channels like branches, ATMs, call-center, online- and mobile-banking offer the possibility to perform such account inquiries. However, opportunity costs like traveling to a branch or ATM, calling the bank's call-center or booting up a PC diminish when a client starts to use the bank's mobile-banking app. As most customers carry a mobile phone in their pocket, information about the current financial situation is only a tab or swipe away and opportunity costs of an account inquiry decrease distinctly. As a consequence, we assume that financial attention should increase after mobile-banking adoption. Due to our knowledge, we are the first who find more frequent account inquiries and therefore increased financial attention after mobile-banking adoption by analyzing transaction data from a bank.

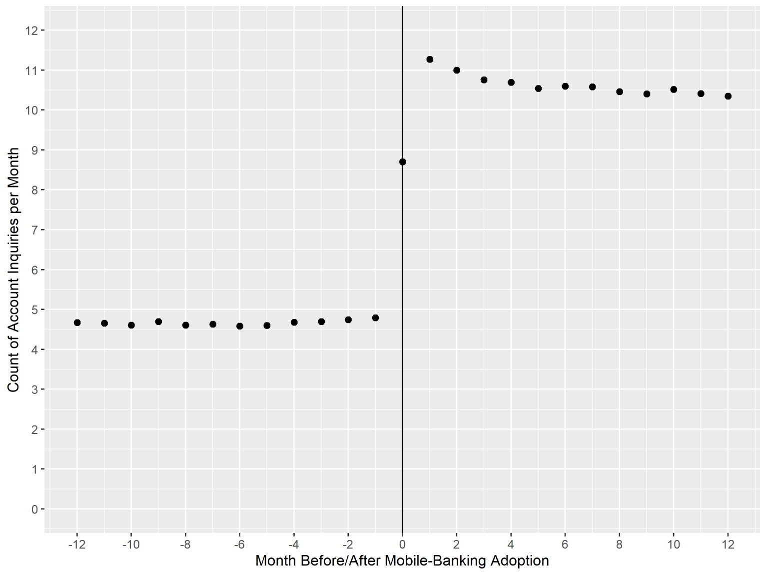

Figure A-3: Number of account inquiries 12-month before/after mobile-banking adoption. X-axis gives the month before/after individual mobile-banking adoption. Y-axis plots the number of monthly account inquiries through any channel. Basis are all 7,990 customers, who adopt mobile-banking during our 22-month observation window.

Figure A-3 visualizes the number of monthly account inquiries 12-months prior to 12-months after mobile-banking adoption. Basis are all 7,990 customers, who adopt mobile-banking during our 22-month observation window. While the average adopter proceeds 4.7 monthly account inquiries prior to her mobile-banking adoption, this value more than doubles to 10.4 after adoption. Figure A-4 breaks the overall sum of monthly inquiries down into different channels. It shows that this increase in financial transparency is clearly driven by inquiries through the mobile-channel, which jump from zero to an average of 8.3 inquiries per month. Account inquiries via online-banking get substituted slightly, as the average of monthly online-banking account inquiries decline from 2.3 to 1.9. Moreover, we can observe a strong reduction in monthly account inquiries through ATMs, which drop from 2.5 before to 1.0 after mobile-banking adoption. Thus, clients use their mobile devices to monitor their financial situation additionally to their online-banking access. This finding is in line with Levi and Benartzi (2020), who document an increase in mobile inquiries and stable PC inquiries after fintech mobile app adoption, and Federal Reserve Board (2016), who report that mobile-banking users check their account balance before making a large purchase, which would be impossible or very costly to proceed via other channels.[3] In marked contrast to almost stable online-banking inquiries, we investigate a strong substitution of ATM usage with respect to observing the actual financial status. Hence, the need for offline account inquiries seems to diminish after mobile-banking adoption, which is in line with Becker et al. (2020), who report substitution of transactions via branches, call center and ATMs after mobile-banking adoption.

3 Mobile-banking seems to provide financial transparency during times or in locations in which it is impossible or too costly to obtain through other channels. For example, if a client would like to inquire her actual account balance during a shopping trip, she would have to call the call-center of the bank, travel to a branch, ATM or e.g. an internet cafe to get access to the online-banking interface.

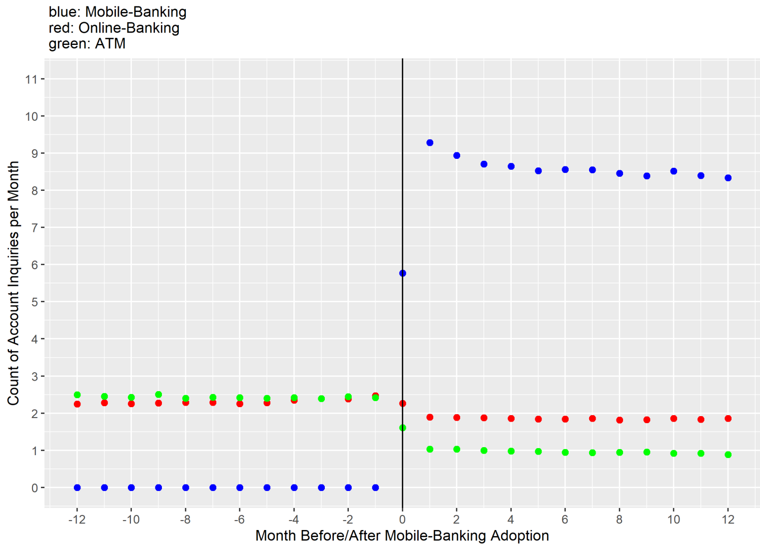

Figure A-4: Account inquiries 12-month before/after mobile-banking adoption differentiated by channels. X-axis gives the month before/after individual mobile-banking adoption. Y-axis plots the number of monthly account inquiries per channel, divided into mobile-banking (blue dots), online-banking (red dots) and ATM (green dots). Basis are all 7,990 customers, who adopt mobile-banking during our 22-month observation window.

For a multivariate investigation of these univariate findings we run the following linear probability model

$$Y_{i,t} = \beta_1 Adoption_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t} \tag{1}$$

where the outcome variable $Y_{i,t}$ is an indicator variable which equals one, whether customer i inquires her financial status at day t, and zero otherwise. *Adoption* denotes an indicator variable, which equals 0 (1) before (after) mobile-banking adoption of individual i at day t. X represents a vector consisting of different control variables. As we examine a potential correlation between financial attention and overdraft behavior, we control for actual overdraft by integrating an indicator variable which equals one, if i faces overdraft at t, and zero otherwise. Furthermore, Olafsson and Pagel (2019) detect that financial attention, measured by logins at an icelandic fintech, increases during days with salary payments while it decreases in spending. Hence, we control for whether or not there was a salary payment or any other money in- or outflow by integrating three additional indicator variables. These values, again, are measured for every customer i at day t. By including η and γ, we calculate individual and time fixed-effects, respectively. Therefore, we compare every customer with herself and estimate a within effect. Standard errors are clustered at the individual level. Similar models are used by Gathergood et al. (2020); Levi and Benartzi (2020); Olafsson and Pagel (2019); Alan et al. (2018); Sicherman et al. (2016); Stango and Zinman (2014); Morgan et al. (2012).

Table A-4 provides results of regression (1). Column (1) documents the basic regression, which includes the adoption dummy ($Adoption_{i,t}$) complemented by individual (η_i) and time fixed-effects (γ_t). Column

	(1)	(2)
Mean (LHS)	0.1753	0.1753
Mobile-Banking		
Adoption	0.1994***	0.1961***
	(0.0005)	(0.0005)
Controls		
Overdraft		-0.0036^{***}
		(0.0002)
Salary		0.0729***
		(0.0003)
Money Inflow		0.1033***
		(0.0002)
Money Outflow		0.1576***
		(0.0001)
Individual Fixed-Effects	Yes	Yes
Time Fixed-Effects	Yes	Yes
Num. obs.	59, 299, 920	59, 299, 920
R^2	0.2055	0.2365
Adj. R^2	0.2040	0.2351

Table A-4: Table documents the association of mobile-banking adoption with daily account inquiries. The dependent variable in both regressions is a binary variable indicating whether or not the customer inquires her accounts at the observed day through any channel (mobile-banking, online-banking, ATM). Adoption equals 0 (1) before (after) individuals mobile-banking adoption, respectively. Overdraft equals 1, whether the account faces overdraft at the observed day, and zero otherwise. Salary equals 1, whether the client receives salary payments at the observed day, and zero otherwise. Money Inflow equals 1, whether the client receives money inflows except of salary payments at the observed day, and zero otherwise. Money Outflow equals 1, whether the account faces money outflows at the observed day, and zero otherwise. Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

(2) adds our control variables Overdraft, Salary, Money Inflow and Money Outflow. In line with Figures A-3 and A-4, Table A-4 documents a strong increase in account inquiries after mobile-banking adoption. Both the basic regression in column (1) as well as the controls-integrating regression in column (2) show statistically and economically highly significant coefficients of 0.1994 and 0.1961, respectively, for mobile-banking adoption on daily account inquiries. Therefore, the full model unveils that after mobile-banking adoption the probability of a daily account inquiry increases by 112% relative to the sample mean (0.1961 / 0.1753 = 1.12). Hence, we document a positive association of mobile-banking adoption with increased financial transparency, measured by a distinct gain in clients probability of a daily account inquiry.

Our control variables show significant results, as well. During days with overdraft, the probability of an account inquiry decreases slightly by -0.36%. During days with salary payments, money in- and outflows we examine contrary effects and observe more frequent account inquiries: The probability of an account inquiry increases by 7.29% during days with salary payments, by 10.33% during days with other money inflows (except of salary payments) and by 15.76% during days with money outflows. We will discuss the association of these control variables in conjunction with the probability of a daily account inquiry in section 2.6.1 in more detail.

Our results regarding changes in clients account inquiry behavior after mobile-banking adoption are consistent with inattention theory. If customers would be always attentive, account inquiries would not change after mobile-banking adoption. However, we will examine whether account inquiries are driven by rational or selective arguments in section 2.6.1 in more detail. Furthermore, these results are in line with the customer contact approach of Chase (1981). Mobile-banking offers anytime and anywhere contact to the bank. Clients do not have to travel to a branch, consider opening times, be on hold in the call center or boot up a PC in order to utilize online-banking anymore. Mobile-banking services are typically highly available, quick and easy to use. Hence, the required effort to inquire current account balances declines distinctly. Following the customer contact approach, this leads to an increase in the efficiency of the service facility (the bank) and should lead to changes in service consumption of the customer, which we find in form of more frequent account inquiries. Finally, our findings are consistent with related studies observing fintech users. For example, Carlin et al. (2019) as well as Levi and Benartzi (2020) use data from account-aggregating fintechs and investigate customers, who use the fintech's PC app and adopt the mobile app during their observation period. Afterwards, they document resulting changes, for instance in login frequency. Carlin et al. (2019) observe that customers propensity to log in each month spikes from roughly 10% to 40% after the app of the observed fintech was made available. Levi and Benartzi (2020) examine the number of monthly logins and find that they increase from 4 times per month prior to mobile app adoption to the number of 10 to 16 times per month, depending on the point in time of client's adoption.

2.5 Effect of Mobile-Banking Adoption on Customers Liquidity Management

2.5.1 Avoidance of Overdraft

Section 2.4 outlines that mobile-banking adoption increases customers financial transparency. Next, we will explore whether and, if so, how customers are able to improve their liquidity management capabilities on the basis of this increase in financial attention. 62% of U.S. mobile banking users check their account balances on their phones before making a large purchase. Half of them decide not to purchase an item as a result of their account balance or credit limit (Federal Reserve Board, 2016). Levi and Benartzi (2020) investigate that clients decrease their spending on discretionary items by 11.6 percentage points after the installation of a fintech's mobile app, which translates into reductions of around $430 per month. Additionally, Olafsson and Pagel (2019) detect that individuals, who use a fintech's online financial aggregation platform via browser or app, are able to predict their future balances up to bins of approximately $50. We build on this literature and examine, whether mobile-banking strengthens customers ability to avoid overdraft.

Usually all regular payments like salary, rental, loan and membership payments, saving rates, daily life consumption etc. proceed at least once in a month. Through aggregation of our daily observations to a monthly data set we receive a financial cycle, which covers all of those regular payments. Based on the above literature, which shows that mobile-banking adopters stronger avoid purchases that would exceed current account balances as well as improve their capabilities of predicting future account balances, we expect that overdraft should be used less frequently to fund monthly liabilities after mobile-banking adoption. By using our monthly aggregated data set, we are able to investigate whether or not mobile-banking adopters are able to completely avoid overdraft after their adoption.

To study the effect of mobile-banking adoption on overdraft avoidance, we run the following regression

$$Y_{i,m} = \beta_1 Adoption_{i,m} + \alpha X_{i,m} + \eta_i + \gamma_m + \epsilon_{im}, \tag{2}$$

where the outcome variable $Y_{i,m}$ is an indicator variable which equals one, whether customer i faces overdraft in month m, and zero otherwise. The right side of regression (2) is similar to regression (1). *Adoption* is, again, an indicator variable, which equals 0 (1) before (after) mobile-banking adoption. X represents a vector consisting of different control variables. According to Alan et al. (2018), we control for whether or not there was an overdraft in the previous month. Because higher (lower) salary payments could lower (heighten) demand for overdraft to fund monthly liabilities, respectively, we add the sum of salary payments in that particular month, as well. In order to consider the frequency of overall account usage in that month, we add the sums of days with inquiry (through any channel), money-inflows and money-outflows. Beside of decreasing spending on (discretionary) items, clients could transfer savings for the purpose of funding spending or use credit cards in order to benefit from their liquidity effect. As these strategies could be used to reach the desired overdraft avoidance, we likewise control for these variables. By including η and γ, we incorporate individual and time fixed-effects. Standard errors are, again, clustered at the individual level.

Table A-5 provides results of regression (2). A sample mean of 0.2969 shows that roughly 30% of all monthly observations represent at least one day with overdraft. We observe a significant reduction of -9.26% in monthly overdraft probability relative to the sample mean after mobile-banking adoption (-0.0275 / 0.2969 = -0.0926). Mobile-banking adoption assists customers to avoid future overdraft distinctly.

Analogous to Alan et al. (2018), one major and positive associated control is whether or not the customer faced overdraft in the previous month. A remarkably high influence has Days with Savings Transactions.

	(1)	(2)
Mean(LHS)	0.2969	0.2969
Mobile-Banking		
Adoption	-0.0182^{***}	-0.0275^{***}
	(0.0024)	(0.0025)
Controls		
Overdraft in Previous Month		0.2654^{***}
		(0.0013)
Salary in Month		0.0000
		(0.0000)
Days with Inquiry		0.0023^{***}
		(0.0001)
Days with Money-Outflows		-0.0008^{***}
		(0.0001)
Days with Money-Inflows		-0.0006^{**}
		(0.0002)
Days with Savings Transactions		0.0363^{***}
		(0.0005)
Days with credit card Transactions		-0.0007^{**}
		(0.0003)
Individual Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Num. obs.	1,954,096	1,844,828
R^2	0.6436	0.6751
Adj. R^2	0.6225	0.6547

Table A-5: Table documents the association of mobile-banking adoption with monthly overdraft behavior. The dependent variable in both regressions is a binary variable indicating whether or not the customer faced overdraft in the observed month. Adoption equals 0 (1) before (after) individuals mobile-banking adoption, respectively. Overdraft in Previous Month equals 1, whether the client faced overdraft in the previous month, and zero otherwise. Salary in Month aggregates all salary payments in euro, which the customer received in the particular month. Days with Inquiry, Money-Outflows, Money-Inflows, Savings Transactions and Credit Card Transactions represent the number of days at which the client inquired her account, disposed money outlows, received money inflows, transferred money from savings accounts and performed credit card payments, respectively. Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

Since the effect is associated positively we conclude that savings accounts transfers are not used to avoid overdraft but rather to reduce overdraft, once the account is overdrafted (reverse causality). We will check this in section 2.5.2 in more detail. A similar assumption can be made regarding the positive effect of Days with Inquiry. Again, customers could inquire their accounts more frequently during times of financial distress and, thus, more continuous account inquiries are not the reason of a higher demand for overdraft. We will check this phenomenon in section 2.6.1 in more detail. Other controls result in a marginal impact with trends in line with our expectations, which we provide for reasons of completeness.

Our results are in line with prior literature and consistent with our expectations. This literature assumes that clients use their mobile-banking app, besides others, to check their account balances before making a large purchase (Federal Reserve Board, 2016), improve their capabilities in predicting future account balances (Olafsson and Pagel, 2019) and reduce discretionary spending after mobile app adoption (Levi and Benartzi, 2020). We add up to these findings and show that customers are also able to stronger avoid overdraft after mobile-banking adoption.

2.5.2 Liquidity Management During Times of Ovedraft

Besides the possibility of completely avoiding overdraft, as documented in section 2.5.1, mobile-banking could also improve financial decision-making during times of overdraft. By this, clients could prevent additional overdraft. Based on prior literature, we can outline three possible strategies that would be beneficial for customers during times of overdraft.

Effects of Mobile-Banking on Spending Behavior

A client could reduce her spending once the account is overdrafted. Prior literature documents different findings on how individuals increase, reduce or smooth consumption spending. Baugh et al. (2021) show that households exhibit an asymmetry in consumption. While they increase their spending following expected tax refunds, as if they would face liquidity constraints, the same households do not reduce consumption spending after they have to make tax payments. Furthermore, households with tax payments do not adjust consumption down during months prior their tax payments. In contrast, these households smooth consumption through tax payments by transferring about a third of the anticipated payment in the month before making the payment. However, even though tax payments do not seem to be associated with a drop in consumption, other studies find situations in which clients reduce their consumption spending. Garmaise et al. (2020) document that consumers cut back discretionary spending on negative macro-economic news. They find that an announcement of a 12-month maximum in the local unemployment rate is associated with a 2% drop in discretionary spending in the two weeks after the announcement. Furthermore, Ganong and Noel (2019) study the sensitivity of spending to income by analyzing how clients change spending after a large and predictable decrease in income, measured by the exhaustion of unemployment insurance benefits. Even though customers could predict the exhaustion quite reasonably, they fail to save in anticipation of the predictable income decline. In contrast, they reduce spending by 12% after exhaustion of the unemployment insurance benefits.

We add up to this literature by examining how consumption spending is linked to overdraft and how this linkage is associated with increased financial transparency after mobile-banking adoption. Types of spending vary in how ordinary they are dispensable. As expenses like rent, loan or insurance rates, membership dues etc. are usually linked to contracts and, hence, are difficult to reduce short dated, it is much simpler to cut spontaneous consumption payments for restaurants, cinemas, retailers etc. Our data provides information about daily money in- and outflows, but these spending are uncategorized.

Fortunately, we receive monthly aggregated data about payment categories for each individual. By this, we are able to approximate the daily amount of consumption spending, which is comparable to the denomination of discretionary spending out of other studies (Garmaise et al., 2020; Levi and Benartzi, 2020). For our approximation we include all payments initiated via debit cards or credit cards that are categorized as consumption spending by the banks system. Furthermore, we have to consider that cash is mainly used at the point of sale of a merchant (Wakamori and Welte, 2017). Hence, we denote that most cash payments are also used to fund personal consumption. We calculate monthly proportions of consumption spending for each customer by adding up the relative share of debit cards and credit cards consumption spending supplemented by monthly cash withdrawals via branches and ATMs. Afterwards, we multiply the individual proportion of consumption spending with daily money outflows. By this, we are able to indicate daily consumption spending, which amount to 41.06€ on average (see Appendix 2.9.2 for a more detailed description of our approximation).

Subsequently, we analyze if such consumption spending is reduced during times of overdraft and whether mobile-banking adoption is associated with this potential reduction. For this purpose, we use the following regression model

$$Y_{i,t} = \beta_1 Adoption_{i,t} + \beta_2 Overdraft_{i,t} + \beta_3 Adoption_{i,t} * Overdraft_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}, \qquad (3)$$

where $Y_{i,t}$ corresponds to the log of consumption spending of customer i at day t. Regression (3) builds on regression (1) and adds an additional indicator variable $Overdraft_{i,t}$ which equals one, if the account of customer i is overdrafted at day t, and zero otherwise. β_1 refers to the percentage change in consumption spending after mobile-banking adoption.[5] β_2 documents clients percentage change in consumption spending during times of overdraft compared to those times without overdraft. By calculating $\exp(\beta_2 + \beta_3)$ - $\exp(\beta_2)$ we can derive, how mobile-banking adoption changes the semielasticity of overdraft on clients consumption spending (Shang et al., 2017). Observing this potential change is of our main interest, as it documents whether mobile-banking adopters further decrease consumption spending during times of overdraft relative to the time before adoption. We denote this effect as Δ Adoption on Overdraft.

In order to observe not only changes during the post adoption period in total but also particularly during those days at which the client uses mobile banking, we run the following regression

$$Y_{i,t} = \beta_1 Inquiry_{i,t} + \beta_2 Overdraft_{i,t} + \beta_3 Inquiry_{i,t} * Overdraft_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}. \qquad (4)$$

Regression (4) builds on regression (3). Instead of $Adoption_{i,t}$ we integrate an indicator variable $Inquiry_{i,t}$ which equals one, whether customer i inquires her account at day t via mobile-banking, and zero otherwise.

5 In a log-linear model $\exp(\beta)$ gives the percentage change in Y for a one-unit increase in the related covariate. However, a rather small β can be interpreted directly, as $\exp(\beta) \approx 1 + \beta$ (Benoit, 2011).

	log Consumption Spending				log Credit Card Spending				log Savings transfers		
Mean(LHS)	1.3075				0.3920				0.1756		
Mean(exp(LHS))	41.0582				10.5973				22.1250		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mobile-Banking & Overdraft											
Adoption	0.0585***	0.0736***	0.0711***		0.0199***	0.0160***	0.0161***		−0.0003	−0.0019	
	(0.0021)	(0.0021)	(0.0021)		(0.0035)	(0.0035)	(0.0035)		(0.0053)	(0.0053)	
Overdraft		−0.1205***	−0.1064***	−0.1259***		0.0066***	0.0079***	0.0110***			
		(0.0010)	(0.0009)	(0.0008)		(0.0015)	(0.0015)	(0.0013)			
Adoption * Overdraft		−0.0905***	−0.0918***			0.0192***	0.0189***				
		(0.0017)	(0.0017)			(0.0027)	(0.0027)				
Inquiry				0.2097***				0.0466***			0.1222***
				(0.0013)				(0.0020)			(0.0026)
Inquiry * Overdraft				−0.0648***				0.0336***			
				(0.0024)				(0.0040)			
Controls											
Salary			0.1720***	0.1659***			0.0068**	0.0054*		0.0467***	0.0432***
			(0.0015)	(0.0015)			(0.0022)	(0.0022)		(0.0049)	(0.0049)
Money Inflows			0.4344***	0.4303***			0.0417***	0.0405***			
			(0.0011)	(0.0011)			(0.0015)	(0.0016)			
Money Outflows							−0.0231***	−0.0235***		0.1990***	0.1976***
							(0.0010)	(0.0010)		(0.0014)	(0.0014)
Credit Card Payment			0.1414***	0.1394***						0.0005	−0.0006
			(0.0019)	(0.0019)						(0.0034)	(0.0034)
Savings Transactions			0.7322***	0.7283***			−0.0155***	−0.0165***			
			(0.0028)	(0.0028)			(0.0036)	(0.0036)			
Δ Adoption on Overdraft		−0.0767	−0.0789			0.0195	0.0193				
Δ Inquiry on Overdraft				−0.0553				0.0346			
Num. obs.	59,299,920				12,020,090				4,283,870		
R^2 (full model)	0.3743	0.3747	0.3798	0.3800	0.1723	0.1723	0.1724	0.1725	0.0764	0.0821	0.0827
Adj. R^2 (full model)	0.3731	0.3735	0.3786	0.3789	0.1705	0.1705	0.1706	0.1707	0.0690	0.0747	0.0754
Individual Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table A-6: Association of mobile-banking adoption and customers financial behavior during times of overdraft. The dependent variables are log of consumption spending in regressions (1) to (4), log of credit card spending in regression (5) to (8) and log of transfers from savings accounts in regressions (9) to (11). Mean(LHS) provides the mean value of the left hand side variable. Mean(exp(LHS) provides the mean value of the retransformed left hand side variable of our log-linear models. All variables are indicator variables. *Adoption* equals 0 (1) before (after) mobile-banking adoption. *Overdraft* equals 1, if the account is overdrafted, and zero otherwise. *Inquiry* equals one, whether the account is inquired via mobile-banking, and zero otherwise. *Salary* equals one, whether there is a salary inflow, and zero otherwise. *MoneyInflows* equals one, whether there is a money inflow except of salary, and zero otherwise. Money Outflows (Credit Card Payment) equals one, whether there is a money outflow (credit card payment), and zero otherwise, respectively. Savings Transactions equals one, whether the client performs a transfer from a savings account, and zero otherwise. Δ Adoption (Δ Inquiry) correspond to $\exp(\beta_2 + \beta_3)$ - $\exp(\beta_2)$ and show, how mobile-banking adoption (an inquiry via mobile-banking) changes the semielasticity of overdraft on the dependent variable, respectively (Shang et al., 2017). Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

This regression complements our insights of regression (3) and indicates robustness of our findings. By calculating $\exp(\beta_2 + \beta_3)$ - $\exp(\beta_2)$ we can derive, how an account inquiry via mobile-banking changes the semielasticity of overdraft on clients consumption spending (Shang et al., 2017). We denote this effect as Δ Inquiry on Overdraft.

Table A-6 presents results regarding the association of mobile-banking adoption with consumption spending in the columns (1) to (4). Mean(exp(LHS)) provides the mean value of the retransformed left hand side variable and shows that a client spends on average 41.06€ for daily consumption.[6] Column (1) shows our basic regression and documents that mobile-banking adoption is associated positively with consumption spending. This basic model documents that a customer increases consumption spending by 5.85% ($\beta_1 = 0.0585$) after mobile-banking adoption. The regression presented in column (2) includes our overdraft indicator variable. Our main regression in column (3) adds controls and shows that consumption spending increases by 7.11% ($\beta_1 = 0.0711$) during times of positive account balances while it decreases by -10.64% ($\beta_2 = -0.1064$) during times of overdraft. Mobile-banking adoption reduces consumption spending during times of overdraft by additional -7.89 percentage points (Δ Adoption on Overdraft $=$ $\exp(\beta_2 + \beta_3)$ - $\exp(\beta_2)$ $=$ -0.0789), which results in a total decrease of -18.53% ($-0.1064 - 0.0789 = -0.1853$). Therefore, mobile-banking strengthens the reduction in consumption spending during times of overdraft by +74% (-0.0789 / -0.1064 = 0.7415). Results of column (4) support this finding by showing that an account inquiry via mobile-banking at a day with overdraft is associated with a -5.53 percentage points decrease in consumption spending at that particular day (Δ Inquiry on Overdraft $=$ $\exp(\beta_2 + \beta_3)$ - $\exp(\beta_2)$ $=$ -0.0553).

These findings add up to literature in several ways. First, we find that customers reduce consumption spending by roughly 11%, once the account is overdrafted. This insight is in line with Garmaise et al. (2020), showing that consumers cut back discretionary spending by 2% in the two weeks after negative macro-economic news, and Ganong and Noel (2019), documenting a reduction in spending by 12% after exhaustion of the unemployment insurance benefits. Second, previous studies examining fintech adoption reveal mixed results. On the one side, Becker (2017) finds an increase in both money in- and outflows after adoption of a money management fintech. He denotes higher saving rates as well as increased spending as the main reasons of higher money outflows. On the other side, Levi and Benartzi (2020) document that customers, who adopt the mobile app of the observed fintech, reduce discretionary spending by -11.6% during the 12 months after mobile app adoption. Our study links consumption spending with overdraft and mobile-banking adoption and documents that considering the actual account balance is of major relevance for explaining these heterogeneous findings. In line with Becker (2017), clients increase their consumption spending by 7.11% ($\beta_1 = -0.0711$) after mobile-banking adoption and during times of

6 The left hand side variable in our log-linear model is log-transformed and stands for log of consumption spending in this section. Mean(exp(LHS)) provides the mean of the retransformed value.

positive account balances. In line with Levi and Benartzi (2020), clients decrease consumption spending by additional -7.89 percentage points in times of overdraft.

Effects of Mobile-Banking on Credit Card Usage

A stronger utilization of credit cards is another liquidity preserving strategy, which could be supported by mobile-banking adoption. Stango and Zinman (2009) propose that 60% of overdraft fees would be avoidable, if people use their credit cards more reasonable or transfer liquidity from savings accounts. By using credit cards more reasonably, customers could cause a delay in payments and therefore generate a positive liquidity effect. Becker et al. (2020) show that mobile-banking adoption and Carlin et al. (2019) that mobile app adoption of a fintech is associated with stronger credit card utilization. The latter suggest that this could be because of attempts to reduce overdraft. Unfortunately, they have to state that such an analysis is not possible on the basis of their data. We take up this point of investigation and examine, whether clients use their credit cards more intensively during times of overdraft in order to benefit from the credit card's liquidity effect and if so, whether mobile-banking intensifies this behavior. For that reason we derive a subsample of 12,020,090 observations, including all customers, who possess a credit card with available spending limit at our research site. We use regressions (3) and (4) with the log of credit card spending as the dependent variable and present results in Table A-6 in columns (5) to (8).

Once again, we start our interpretation with a basic regression in column (5), which shows that the volume of credit card spending increases by 1.99% ($\beta_1 = 0.0199$) after mobile-banking adoption. The regression presented in column (6) adds the overdraft indicator variable and regression presented in column (7), which is of our main interest, further integrates controls. This regression unveils that customers increase their credit card spending by 0.79% ($\beta_2 = 0.0079$) during times of overdraft. Even though this is just a marginal increase it is still beneficial, as credit cards provide a liquidity effect that avoids additional overdraft. However, credit card spending during times of overdraft increases by additional 1.93 percentage points (Δ Adoption on Overdraft = $\exp(\beta_2+\beta_3)$ - $\exp(\beta_2) = 0.0193$) to 2.72% ($0.0079 + 0.0193 = 0.0272$) after mobile-banking adoption, which corresponds to an improvement of 244% ($0.0193/0.0079 = 2.44$) in this liquidity preserving strategy. Hence, mobile-banking improves clients ability to make use out of the credit card's liquidity effect in order to avoid further overdraft. Results in column (8) provide further support for these findings, as they outline that an account inquiry via mobile-banking at days with overdraft is associated with a 3.46 percentage points (Δ Inquiry on Overdraft = 0.0346) increase in credit card spending at that particular day.

These insights complement findings out of prior literature. Similar to our results, Becker et al. (2020) and Carlin et al. (2019) document stronger credit card utilization after mobile-banking and mobile app adoption of a fintech, respectively. Most recently, researches are unaware of the drivers of this gain in credit card spending. We contribute to this stream of literature by showing that increased credit card

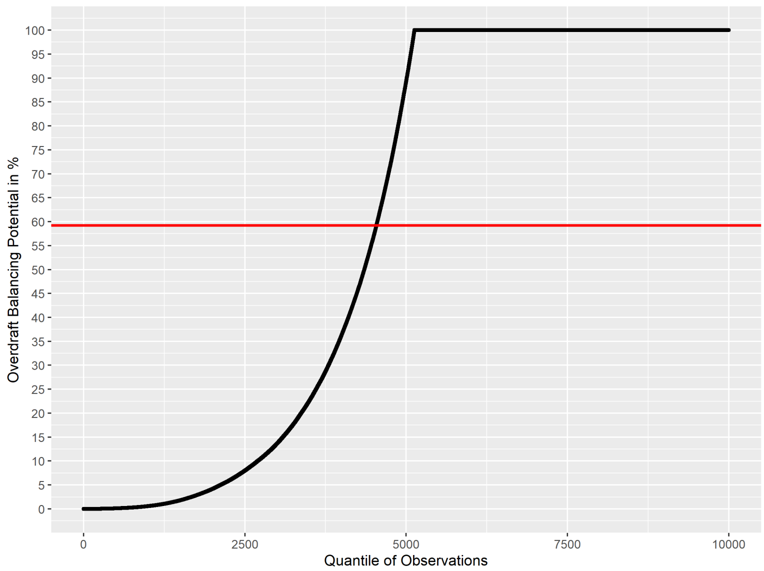

Figure A-5: Visualization of overdraft balancing potential. X-achsis groups the observations into 10,000 quantiles, y-achsis plots the proportion of overdraft that could be balanced by savings accounts transfers. The red line corresponds to the mean value of the y-achsis. Basis is the subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts.

usage after mobile app adoption results at least partially out of attempts to avoid (further) overdraft. By this, clients make use out of the credit cards liquidity effect.

Effects of Mobile-Banking on Savings Transfers

Customers could transfer liquidity from their savings accounts to balance overdrafted current accounts (Stango and Zinman, 2009). Such a behavior would be beneficial, as savings accounts offer only marginal interest rates compared to the costly checking account overdraft. For our analysis, we derive a subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts.[7] Figure A-8 divides this subsample into 10,000 quantiles and visualizes the proportion of overdraft that could be balanced directly by transferring money from savings accounts. As shown by the red line, 59.69% of the overall overdraft amount could be balanced and roughly 50% of all observations could compensate their overdraft completely. Although all customers in this subsample have been able to settle their overdrafted account at least partially, Figure A-9 unveils that only 3.28% of those observations availed this opportunity. This value splits up in 0.78%, who fully, and 2.50%, who partially balanced their overdraft. In line with Stango and Zinman (2009), we have to state that most customers do not balance costly overdraft by transferring liquidity from low-interest savings accounts. Subsequently, we analyze whether this financial mistake can be reduced after mobile-banking adoption. We use regression (1) with the log of transfers from savings accounts of customer i at day t as

7 We define overdraft in this analysis by taking the end-of-day current account balance and subtract all savings accounts transfers on that particular day, because these transfers could already be intended to balance eventual overdraft. If this calculation results in a negative account balance, we denote the account as overdrafted.

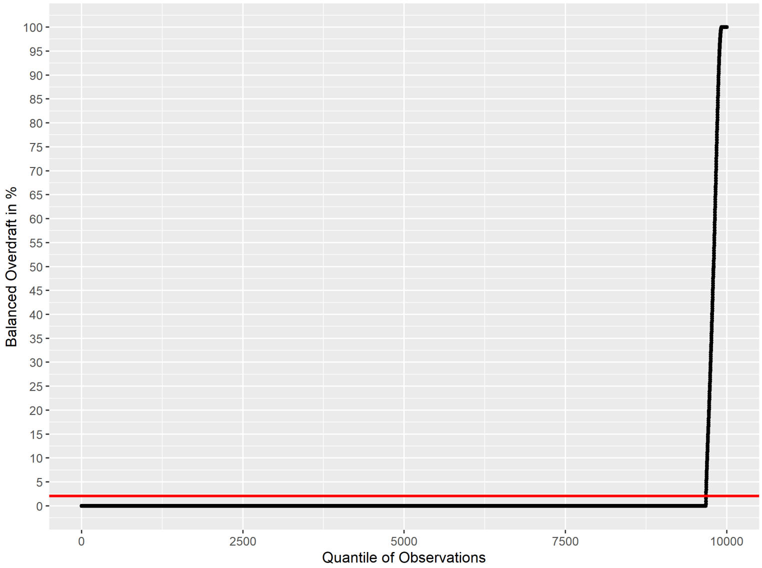

Figure A-6: Visualization of balanced overdraft. X-achsis groups the observations into 10,000 quantiles, y-achsis plots the proportion of overdraft balanced by savings accounts transfers. The red line corresponds to the mean value of the y-achsis. Basis is the subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts.

our dependent variable $Y_{i,t}$. Furthermore, we run the following regression

$$Y_{i,t} = \beta_1 Inquiry_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}, \tag{5}$$

which builds on regression (1), but instead of $Adoption_{i,t}$ we integrate our indicator variable $Inquiry_{i,t}$ of regression (4).[8] Furthermore, we include several indicator variables, which could diminish the need for a certain liquidity preserving strategy, into the control vector X of our regressions. These control variables can be found in Table A-6 in the controls-panel. Salary (Money Outflows) [Credit Card Payment] equals one, whether there are salary inflows (money outflows) [credit card payments] at the observed day, and zero otherwise, respectively. By performing regressions (1) and (5) with log of transfers from savings accounts as our dependent variable, we investigate whether the amount of savings transfers during times of overdraft is associated with mobile-banking adoption in general as well as account inquiries via mobile-banking in particular, respectively. We present our results in Table A-6 in columns (9) to (11).

The basic regression documented in column (9) as well as the controls-including regression presented in column (10) show that mobile-banking adoption solely seems not to be linked to changes in client's transfer behavior during times of overdraft, as the β_1 coefficient in both regressions is not significant. However, as documented in column (11), a mobile-banking account inquiry at a day with overdraft is associated with a 12.22% ($\beta_1 = 0.1222$) increase in transfers from savings accounts. Hence, mobile-banking supports clients in realizing their potential of balancing costly overdraft by using liquidity from low-interest savings

8 Regressions (1) and (5) correspond to regressions (3) and (4) without the indicator variable $Overdraft_{i,t}$ and the associated interaction term $Adoption_{i,t} * Overdraft_{i,t}$ and $Inquiry_{i,t} * Overdraft_{i,t}$, respectively.

accounts during those days, at which the client inquires the account via mobile-banking.

2.5.3 Heterogenous Treatment Effects for Offliners and Onliners

Sections 2.4 and 2.5 provide results on how mobile-banking adoption is related to higher financial transparency, measured in more frequent account inquiries, and improved financial decision-making capabilities, documented in reduced demand for costly checking account overdraft. Up to now, our findings do not differentiate between clients prior usage of other banking channels. However, we have to take into account that some of our observed customers already use online-banking, which stands for the most popular digital banking channel, while others do not. As a consequence, some customers benefit already from digital banking services and are potentially better informed than those customers, who formerly did not utilize digital banking channels. If so, the latter ones could benefit stronger from mobile-banking adoption.

Prior mobile-banking literature frequently studies changes for digital fintech users, who start to use a mobile app (Carlin et al., 2019; Levi and Benartzi, 2020). But, in 2017 37% of the US citizens do not use online-banking at all and around 45% state that branches and ATMs are the primary method to access their bank accounts. The fraction of similar clienteles in the German population is even higher: In 2017 only 57% do use online-banking and therefore 43% still use other channels to stay informed about their financial situation (Federal Deposit Insurance Corporation, 2017; Statistisches Bundesamt, 2018). Hence, a large fraction of the population does not incorporate digital channels for their banking transactions and fintech-based studies face two possible shortcomings: First, they do not receive a random sample, as their observed individuals self-selected into the observed digital platform (Baugh et al., 2021). Second, these studies potentially underestimate aggregate effects of mobile-banking, as the observed customers already benefit from the digital fintech services.

In order to investigate, whether prior online-banking usage potentially affects our findings on mobile-banking adoption, we build an indicator variable *Offliner* which equals one, whether the client has not used online-banking one month prior to mobile-banking adoption, and zero otherwise. Subsequently, we integrate this indicator variable as a moderator into our previous regressions. We denote those customers, who have not used online-banking one month prior to mobile-banking adoption (*Offliner*=1), as Offliners and those clients, who have used online-banking one month prior to mobile-banking adoption (*Offliner*=0), as Onliners. By observing the moderation effect of our indicator variable *Offliner*, we are able to analyze whether Offliners benefit stronger from mobile-banking adoption than Onliners do. If so, we would observe a positive interaction of *Offliner* with the respective effects of interest.

	(1)	(2)	(3)	(4)	(5)
Mean(LHS)	0.1753	0.2969	1.3075	0.3920	0.1756
Mean(exp(LHS))			41.0582	10.5973	22.1250
Prior Covariates of Interest					
Adoption	0.1644***	−0.0257***	0.0511***	0.0152***	
	(0.0006)	(0.0026)	(0.0024)	(0.0037)	
Overdraft			−0.0743***	0.0054**	
			(0.0014)	(0.0019)	
Adoption * Overdraft			−0.1178***	0.0202***	
			(0.0020)	(0.0030)	
Inquiry					0.1220***
					(0.0026)
Moderation through non-prior Online-Banking Usage					
Offliner	−0.0441***		−0.0647***	0.0043	0.0261***
	(0.0006)		(0.0029)	(0.0052)	(0.0077)
Offliner * Adoption	0.1241***	−0.0081	0.0794***	−0.0009	
	(0.0012)	(0.0046)	(0.0047)	(0.0103)	
Offliner * Overdraft			−0.0581***	0.0068*	
			(0.0019)	(0.0029)	
Offliner * Adoption * Overdraft			−0.0947***	0.0489**	
			(0.0078)	(0.0152)	
Offliner * Inquiry					0.0147
					(0.0143)
Δ Adoption on Overdraft			−0.1032	0.0205	
Δ Offliner on Adoption			0.0870	−0.0009	
Δ Offliner on Overdraft			−0.0524	0.0069	
Δ Offliner on Adoption * Overdraft			−0.0803	0.0511	
Δ Offliner on Inquiry					0.0167
Num. obs.	59,299,920	1,844,828	59,299,920	12,020,090	4,283,870
R^2	0.2367	0.6751	0.3798	0.1724	0.0827
Adj. R^2	0.2353	0.6547	0.3786	0.1706	0.0754

Table A-7: Investigation of differences in mobile-banking effects between clients with and without prior online-banking usage. The columns refer to prior objects of investigation of our study. The dependent variables are in column (1) a binary variable indicating whether or not the customer inquires her financial status at the observed day through any channel (mobile-banking, online-banking, ATM), in column (2) a binary variable indicating whether or not the customer faced overdraft in the observed month, in column (3) log of consumption spending, in column (4) log of credit card spending and in column (5) log of transfers from savings accounts at the observed day. Mean(LHS) provides the mean value of the left hand side variable. For columns (3) to (5), mean(exp(LHS) provides the mean value of the retransformed left hand side variable of our log-linear models. All variables are indicator variables. *Adoption* equals 0 (1) before (after) mobile-banking adoption. *Overdraft* equals 1, if the account is overdrafted, and zero otherwise. *Inquiry* equals one, whether the account is inquired via mobile-banking, and zero otherwise. *Offliner* equals one, whether the client has not used online-banking one month prior to mobile-banking adoption, and zero otherwise. Δ Adoption on Overdraft shows, how mobile-banking adoption changes the semielasticity of overdraft on consumption spending and credit card spending, respectively (Shang et al., 2017). Δ Offliner on Adoption * Overdraft shows, how the absence of prior online-banking usage further alters the change in semielasticity outlined by Δ Adoption on Overdraft. Δ Offliner on Inquiry shows, how the absence of prior online-banking usage changes the semielasticity of a mobile-banking account inquiry on changes in savings accounts transfers. Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

Table A-7 shows results of our moderation analysis. Columns (1) to (5) provide our main regressions out of sections 2.4, 2.5.1 and 2.5.2, namely the association of mobile-banking adoption with account inquiries, overdraft avoidance, consumption spending, credit card spending and transfers from savings accounts, respectively, extended by a potential moderation of *Offliner*. As the prior effects of interest in each regression are still significant, we can conclude that both Offliners and Onliners benefit from mobile-banking adoption. However, we find significant moderation of our results regarding the association of mobile-banking adoption with account inquiries, reductions in consumption spending as well as improved credit card spending during times of overdraft. This indicates that the effects of mobile-banking adoption in these research areas are even stronger for Offliners compared to Onliners.

Column (1) shows how *Offliner* affects the effect of mobile-banking adoption on account inquiries through any channel. Our results in section 2.4 unveil that in the full sample the probability of a daily account inquiry increases by 112% relative to the sample mean after mobile-banking adoption. Now we investigate that this effect differs distinctly between Offliners and Onliners. As Onliners probability of a daily account inquiry increases by 94% (0.1644/0.1753 = 0.9378) relative to the sample mean after mobile-banking adoption, Offliners benefit from an increase of 165% ([0.1644+0.1241]/0.1753 = 1.6458) relative to the sample mean. Thus, the effect of mobile-banking adoption on login frequency is roughly twice as strong for Offliners compared to Onliners ([0.1644+0.1241] / 0.1644 = 1.75).

Column (2) reports results of our analysis, whether prior online-banking usage affects the effect of mobile-banking adoption on the ability to avoid overdraft in subsequent months. As we do not observe a statistical significant moderation effect, we conclude that our results documented in section 2.5.1 apply to both Offliners and Onliners equally.

The regression results provided in column (3) show differences in reductions of consumption spending between Offliners and Onliners. In this regression we observe that an *Onliner* without mobile-banking usage reduces her spending by -7.43% (*Overdraft* = -0.0743) during times of overdraft. After mobile-banking adoption an *Onliner* reduces consumption spending during times of overdraft by additional -10.32 percentage points (Δ Adoption on Overdraft = -0.1032) to -17.75%. However, an *Offliner* benefits even stronger. Prior to mobile-banking adoption, she reduces consumption spending during times of overdraft already by additional -5.24 percentage points (Δ Offliner on Overdraft = -0.0524) to -12.67% (-0.0743 - 0.0524 = -0.1267). This reduction in consumption spending further decreases by additional -8.03 percentage points after mobile-banking adoption. Thereby, an *Offliner* in total reduces consumption spending by -31.02% (-0.0743 - 0.1032 - 0.0524 - 0.0803 = 0.3102) during times of overdraft after mobile-banking adoption. Thus, the effect of mobile-banking adoption on reductions in consumption spending during times of overdraft is roughly twice as strong for Offliners compared to Onliners ([-0.1032 - 0.0803] / -0.1032 = 1.78).

With respect to our investigation of credit card utilization during times of overdraft, the results out of column (4) document differences between Offliners and Onliners, too. An *Onliner* increases her credit card spending during times of overdraft by 0.54% (*Overdraft* = 0.0054) prior to a potential mobile-banking adoption. This stronger utilization during times of overdraft rises by additional 2.05 percentage points (Δ Adoption on Overdraft = 0.0205) to 2.59% (0.0054 + 0.0205 = 0.0259) after mobile-banking adoption. However, an *Offliner*, again, benefits even stronger. She already increases credit card utilization during times of overdraft by additional 0.69 percentage points (Δ Offliner on Overdraft = 0.0069) to 1.23% (0.0054 + 0.0069 = 0.0123) prior to a potential mobile-banking adoption. After mobile-banking adoption, this stronger credit card utilization gets further improved by additional 5.11 percentage points (Δ Offliner on Adoption * Overdraft = 0.0511). Thereby, an *Offliner* in total increases credit card spending by 8.39% (0.0054 + 0.0205 + 0.0069 + 0.0511 = 0.3102) during times of overdraft after mobile-banking adoption. Thus, the effect of mobile-banking adoption on credit card utilization during times of overdraft is roughly three times as strong for Offliners compared to Onliners ([0.0205 + 0.0511] / 0.0205 = 3.49).

Column (5) reports results of our analysis, whether transfers from savings accounts change on days with mobile-banking inquiries during times of overdraft. Similar to column two, we do not observe significant moderation effects. Hence, we conclude that our results regarding savings accounts transfers, which we document in section 2.5.2, apply to both Offliners and Onliners equally.

These results add up to literature by showing that prior studies, which examine the association of mobile-banking adoption with financial transparency, changes in consumption spending as well as credit card utilization by analyzing fintech data, potentially underestimate aggregate effects of mobile app adoption (Carlin et al., 2019; Levi and Benartzi, 2020).

2.6 Further Analyses

2.6.1 Do we observe Ostrich Behavior?

Researchers generally agree that personal resources are limited and thus people are not able to learn every information, which is available in the environment. However, there is an ongoing academic discussion regarding the drivers of personal attention. One fraction of researches reckons that attention is driven by rational arguments (so called rational inattention), which results in a sporadically update of information and inattention in between updates (Levi and Benartzi, 2020; Moscarini, 2004; Reis, 2006; Sims, 2003; Nieuwerburgh and Veldkamp, 2009). The other side finds that personal attention is determined by selective drivers and customers try to avoid negative information. Such models are denoted as selective attention, information-, reference- or belief-dependent utility models (Levi and Benartzi, 2020; Olafsson and Pagel, 2019). With respect to financial decision-making, the so called ostrich effect denotes a selective attention behavior in which clients attend or avoid distinct information. Starting with Galai (2006), who realizes that investors in Israel try to avoid apparently risky financial situations by pretending they do not exist, Karlsson et al. (2009) derive a model, which shows that people attend to good news more than to bad news. Koszegi and Rabin (2009) develop a related model and explore that changes in wealth are news about future consumption. Because people like to consume, the recognition of a higher wealth status is more likely than that of a lower one. These concepts find empirical evidence in Sicherman et al. (2016), who investigate that retail investors show less attention to portfolio information during times of market declines or higher volatility. Olafsson and Pagel (2019) extend this body of literature and analyze drivers of fintech logins. They examine that people prevent account inquiries when liquidity is low or spending is high. Hence, their empirical findings indicate that financial attention is driven by selective rather than rational arguments. The results of Levi and Benartzi (2020) are consistent with both rational and selective (in)attention. On the one hand, they find a decrease in spontaneous shopping categories and an increase in fintech logins during retail rush hours, which is more consistent with rational decision-making. On the other hand, they document lower effects in spending behavior and login frequency among lower-income and high spending-to-income consumers, which is rather consistent with selective attention.

We contribute to this stream of literature by observing a potential association of customers liquidity situation including account transactions with her account inquiry behavior. Olafsson and Pagel (2019) detect that fintech logins increase with higher liquidity and during days with salary payments while it decreases in spending. Higher liquidity and salary payments indicate increased consumption possibilities, money outflows instead lead to a decrease in consumption capabilities. Following Koszegi and Rabin (2009), an Ostrich client would generate higher utility in receiving news about increased instead of decreased consumption possibilities. However, a rational agent instead would attend stronger during times of lower liquidity or money outflows, as these could result in financial distress and increased fees, e.g. overdraft fees. Hence, Olafsson and Pagel (2019) conclude that their clients tend to behave like an Ostrich and not like a rational agent. In order to observe whether our clients tend to behave rational or selective (ostrich behavior), we use the following regression

$$Y_{i,t} = \beta_1 Adoption_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}, \tag{6}$$

which is similar to regression (1), and instrumentalize the controls vector X to represent customers liquidity situation. In order to estimate the perceived liquidity situation, we calculate the end-of-day current account balance, divided into individual deciles for every customer. Furthermore, and similar to Table A-4, we add indicator variables measuring whether or not there is a salary payment or any other money in- or outflow.

Table A-8 documents our results. Based on our data we suppose rational instead of selective (in)attention, when it comes to account inquiries. In comparison to the lowest decile of individuals end-of-day account

	(1)
Mean (LHS)	0.1753
Mobile-Banking	
Adoption	0.1961***
	(0.0005)
Liquidity Situation	
EoD Current Account Balance (2)	−0.0067***
	(0.0002)
EoD Current Account Balance (3)	−0.0088***
	(0.0002)
EoD Current Account Balance (4)	−0.0106***
	(0.0002)
EoD Current Account Balance (5)	−0.0118***
	(0.0002)
EoD Current Account Balance (6)	−0.0128***
	(0.0002)
EoD Current Account Balance (7)	−0.0132***
	(0.0002)
EoD Current Account Balance (8)	−0.0131***
	(0.0002)
EoD Current Account Balance (9)	−0.0119***
	(0.0002)
EoD Current Account Balance (10)	−0.0046***
	(0.0002)
Salary	0.0732***
	(0.0003)
Money Inflow	0.1034***
	(0.0002)
Money Outflow	0.1576***
	(0.0001)
Individual Fixed Effects	*Yes*
Time Fixed Effects	*Yes*
Num. obs.	59,299,920
R^2	0.2366
Adj. R^2	0.2352

Table A-8: Table documents the association of mobile-banking adoption with daily account inquiries with focus on potential ostrich behavior. The dependent variable is a binary variable indicating whether or not the customer inquires her accounts at the observed day through any channel (mobile-banking, online-banking, ATM). Adoption equals 0 (1) before (after) individuals mobile-banking adoption, respectively. EoD Current Account Balance represent individual deciles of the end-of-day current account balance for every customer. Salary equals 1, whether the client receives salary payments at the observed day, and zero otherwise. Money Inflow equals 1, whether the client receives money inflows except of salary payments at the observed day, and zero otherwise. Money Outflow equals 1, whether the client faces money outlows at the observed day, and zero otherwise. Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

balance, $Y_{i,t}$ decreases progressively when liquidity is getting higher. Decile 10 deviates a little from the trend initiated by deciles 2 to 9 but is still negative. The coefficients of salary payments, Money In- and Outflows support this perception. For an *ostrich client* we would expect positive increasing regression coefficients in account balances as well as higher coefficients of salary (0.0732) and other money-inflows (0.1034) in comparison to money-outflows (0.1576), as these stand for higher wealth and therefore more extensive consumption capabilities (Koszegi and Rabin, 2009). However, a rational agent should take care more about liquidity reductions in terms of financial planning (Olafsson and Pagel, 2019), which is what we find in our study by observing increasing attention with decreasing liquidity in combination with higher attention to money-outflows (0.1576) compared to money-inflows (0.1034) and salary payments (0.0732).

Our findings stand in contrast to Olafsson and Pagel (2019). One possible explanation could be found in the research site. Olafsson and Pagel (2019) outline that they receive data from an account aggregation fintech, which visualizes account information but is not able to proceed financial transactions like money transfers. However, during times of financial distress a rational agent benefits stronger from a banking channel in which she is able to proceed transactions, e.g. in order to transfer liquidity from savings accounts to balance overdraft as outlined in section 2.5.2. If so, the decrease in fintech logins could be driven by limited capabilities of the platform instead of information-dependent utility of the client. As we receive data from a bank, which is able to aggregate information as well as proceed transactions in all of the observed banking channels, our study seems not be limited to such an effect.

2.6.2 Is Ease of Use a relevant Factor for Savings Transfers?

Popular and intensively studied theoretical frameworks assume that ease of use strongly impacts self-service channel adoption and usage in retail banking. Davis and Davis (1989) denote this aspect as *ease of use* in the *Technology Acceptance Model (TAM)*, Rogers (2003) labels it as *complexity* in the *Innovation Diffusion Theory (IDT)* and Venkatesh et al. (2003) name it as *effort expectancy* in the *Unified Theory of Acceptance and Use of Technology (UTAUT)*. All models aim to measure, how difficult the innovation is to understand and/or to use. Based on this, many survey based studies empirically analyze a potential linkage. Adoption of ATMs (Curran and Meuter, 2005), online-banking (Montazemi and Qahri-Saremi, 2015; Pikkarainen et al., 2004), mobile-banking (Saeed, 2011), mobile-payment (Schierz et al., 2010) and mobile CRM systems (Sangle and Sharma, 2011) are associated with their ease of usage.

Based on this literature it seems likely that our results are associated with ease of use of mobile-banking, as well. With respect to our findings documented in section 2.5.2, we provide further insights regarding a potential association of ease of use with the behavior of transferring liquidity from savings accounts to balance overdraft. In order to measure ease of use of proceeding such money transfers, we consider the method by which the customer generates the second factor to authenticate the transfer, which is required for regulatory reasons. By doing this, we are the first due to our knowledge, who incorporate transaction data to observe facet's of banking channels ease of use.

Our research site offers three transfer authentication methods. First, a customer can use a separate application (*App*) on the mobile phone to generate the transfer authentication number number (TAN), which represents the desired second factor. This method is most convenient for mobile-banking users, because individuals need only one device and the TAN can be copied easily to the banking app. Second, transfer authentication by *Card* is available. To use this method a customer needs a card reader, in which the debit card has to be plugged in. Subsequently, a code, which is generated by the banking app, can be scanned and the card reader provides the TAN afterwards. In comparison to *App*, this method is less convenient with respect to mobile-banking, because a customer needs a debit card and a card reader, additionally to the mobile phone, to receive the TAN. Third, individuals can use the *SMS* method. In the context of mobile-banking the customer has to possess a second mobile phone or tablet for supervisory reasons, to which the SMS can be sent.[9] This method seems to be least comfortable. As a couple of customers have not enabled at least one transfer authentication method, we integrate a fourth category which stands for *No transfer authentication* method.[10] These customers may realize the balancing potential, but they have to use a different channel to transfer money.

In order to observe potential association of the transfer authentication method with overdraft balancing behavior, we use, again, our subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts (see section 2.5.2) and estimate the following regression

$$\begin{aligned} Y_{i,t} = \beta_1 Inquiry_{i,t} \, * \, No\_transfer\_authentication_{i,t} + \beta_2 Inquiry_{i,t} \, * \, SMS_{i,t} + \\ \beta_3 Inquiry_{i,t} \, * \, Card_{i,t} + \beta_4 Inquiry_{i,t} \, * \, App_{i,t} + \alpha X_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}, \end{aligned} \tag{7}$$

which builds on regression 4, expanded by the transfer authentication method. No transfer authentication denotes an indicator variable which equals one, whether there is no transfer authentication method registered for the customer, and zero otherwise. SMS (Card) [App] denote indicator variables which equal one, whether the client uses the SMS- (card-) [app-] based transfer authentication method, and zero otherwise, respectively.[11] $Y_{i,t}$ denominates the log of transfers from savings accounts of customer i at day t. The rest of the regression is as described in section 2.5.2.

Table A-9 provides results of our analysis. We can observe that ease of use, instrumentalized by the generation method of the second factor in payment processing, has a distinct impact on savings transfers via mobile-banking. No transfer authentication and SMS result in slightly similar coefficients. Customers, who do not have registered a transfer authentication method, have to switch to other banking channels like

9 As a SMS can usually be reviewed without typing in an additional password, regulators force banks to send the SMS to a different device.
10 These customers are able to inquire their accounts via mobile-banking but not capable to proceed transactions.
11 In our data, every customer is assigned to exactly one and not to multiple transfer authentication methods.

	log Savings transfers
Mean (LHS)	22.1250
Mobile Banking	
Inquiry * No transfer authentication	0.0832***
	(0.0166)
Inquiry * SMS	0.0766***
	(0.0046)
Inquiry * Card	0.1352***
	(0.0033)
Inquiry * App	0.2244***
	(0.0113)
Controls	
Salary (IV)	0.0433***
	(0.0049)
Money Outflows (IV)	0.1976***
	(0.0014)
Credit Card Payment (IV)	−0.0005
	(0.0034)
Num. obs.	4283870
R^2 (full model)	0.0828
Adj. R^2 (full model)	0.0754
Individual Fixed Effects	*Yes*
Time Fixed Effects	*Yes*

Table A-9: Association of mobile-banking inquiries in combination with customers transfer authentication method and transfers from savings accounts during times of overdraft. The dependent variables denotes log of transfers from savings accounts. All variables are indicator variables. Inquiry equals one, whether the account is inquired via mobile-banking, and zero otherwise. App (Card, SMS) denote indicator variables which equal one, whether the client uses the app- (card-, SMS-) based transfer authentication method, and zero otherwise, respectively. No transfer authentication denotes an indicator variable which equals one, whether the client has not registered any transfer authentication method, and zero otherwise. Salary equals one, whether there is a salary inflow, and zero otherwise. Money Outflows (Credit Card Payment) equals one, whether there is a money outflow (credit card payment), and zero otherwise, respectively. Cameron et al. (2011) robust standard errors, which are clustered at the client level, are provided in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively.

branches, ATMs or call-center to proceed transfers from savings accounts. However, an account inquiry via mobile-banking in this group is still associated with a 8.32% ($\beta_1 = 0.0832$) increase in transfers from savings accounts compared to those days without an inquiry. Customers, who use the SMS method, are also likely to switch to other banking channels, e.g. online-banking, as they would need a second mobile phone for supervisory reasons to authenticate a transfer via mobile-banking. Mobile-banking account inquiries in this group are associated with a comparable 7.66% ($\beta_2 = 0.0766$) increase in savings transfers relative to those days without a mobile-banking inquiry. Clients, who utilize the card method, roughly double their savings transfers in comparison to the first two groups. They result in a 13.52% ($\beta_3 = 0.1352$) increase in savings transfers during days with a mobile-banking account inquiry relative to those days without. The App method seems to be most convenient. Clients, who utilize this method, roughly triple their savings transfers in comparison to the first two groups. They result in a 22.44% ($\beta_3 = 0.2244$) increase in savings transfers during days with a mobile-banking account inquiry in comparison to days without an inquiry.

Hence, ease of use, instrumentalized by the transfer authentication method, is strongly associated with customers ability to use liquidity from savings accounts in order to balance overdraft, which is consistent with our above expectations. Due to our knowledge, we are the first, who incorporate transaction level data from a bank to observe such an association of ease of use with channel utilization.

2.7 Discussion and Conclusion

In this paper we examine that clients attend more frequently to their personal financial situation after mobile-banking adoption. Based on this increase in financial transparency, customers are able to improve financial decision-making in terms of reductions in costly overdraft consumption. Our study takes up recent insights, which state that higher financial transparency can reduce costly overdraft usage (Carlin et al., 2019; Stango and Zinman, 2014), and explores this phenomenon in more detail. By using large scale inidividual-level panel data from a German bank and performing difference-in-differences analysis, we find a substantial increase in financial attention after mobile-banking adoption, as the probability of a daily account inquiry roughly doubles afterwards. This finding complements Levi and Benartzi (2020) as well as Carlin et al. (2019), who examine increased financial attention of fintech users after mobile app adoption.

Moreover, our study adds up to research analyzing dimensions of financial decision-making. Imperfect decisions are a major reason of overdraft consumption (Agarwal et al., 2009; Carvalho et al., 2019; Jørring, 2020; Stango and Zinman, 2009). Our results contribute to the discussion on how to protect consumers from high fees generated by such debt. We document that clients reduce consumption spending and increase credit card utilization during times of overdraft in order to avoid additional overdraft at least to some extent. Thus, clients seem to be aware about their adverse situation and react beneficial. However, mobile-banking adoption supports clients in this behavior. Mobile-banking adopters strengthen the reduction in consumption spending during times of overdraft by +74%. Furthermore, credit card spending during times of overdraft increases by 244% compared to those times prior mobile-banking adoption. Finally, a mobile-banking account inquiry at a day with overdraft is associated with a 12% increase in transfers from savings accounts.

Furthermore, we extend prior insights by showing that notably those customers, who do not use online-banking prior their mobile-banking adoption, benefit in several aspects from mobile-banking adoption the strongest. As in 2017 37% (43%) of the US (German) citizens, respectively, did not use online-banking at all and, hence, employ other channels to stay informed about their financial situation (Federal Deposit Insurance Corporation, 2017; Statistisches Bundesamt, 2018), prior fintech based studies potentially underestimate aggregate effects of mobile-banking.

Our further analyses investigate drivers of financial attention as well as the association of ease of use with mobile-banking utilization. By this, we add up to literature with relevant results. First, our findings are consistent with rational instead of selective (in)attention theory. By this, we contribute to an ongoing academic discussion on whether rational (Levi and Benartzi, 2020; Nieuwerburgh and Veldkamp, 2009; Reis, 2006; Moscarini, 2004; Sims, 2003) or selective (Galai, 2006; Karlsson et al., 2009; Koszegi and Rabin, 2009; Olafsson and Pagel, 2019) arguments drive financial attention. Moreover, prior findings in this area are somewhat puzzling: Recent studies imply that customers are able to reduce overdraft through higher financial transparency (Carlin et al., 2019; Levi and Benartzi, 2020) while they simultaneously do not attend to their financial situation during times of financial distress (Olafsson and Pagel, 2019). Our results instead document that individuals attend not less but stronger during times of financial distress and are, thus, able to reduce adverse overdraft consumption. Second, politicians, regulators and consumer protectors discuss frequently on how to protect retail banking customers from costly overdraft. Based on our results, they should encourage the usage of systems that improve both financial transparency and financial decision-making. For example, with the second Payment Services Directive (PSD2), which came into force in Europe in September 2019 and therefore after our sampling period, regulators exempt payment service providers from the application of strong customer authentication when the payer transfers money to him- or herself (European Banking Authority, 2017, Article 14). Our results show that ease of use, measured by the transfer authentication method which achieves strong customer authentication, is strongly associated with customers ability to use liquidity from savings accounts in order to balance overdraft. Thus, based on our results that change in regulatory policy seem auxiliary and should support clients to balance overdraft by transferring liquidity from low-interest savings accounts.

Eventually, our paper faces several limitations and points out opportunities for further research. First, our data is limited to a single bank. In order to receive more general insights, a multi-bank data set should be incorporated. By this, results could overcome the dependence on the design of a single mobile-banking application. Second, although we perform difference-in-differences techniques and control for several factors it is still possible that our results are determined by unobserved influences, which would undermine our causal interpretation. Third, even if we received comprehensive data on a daily basis, which provide detailed insights into clients behavior, we still face several limitations. On the one hand, we are not able to differentiate money-outflows into categories distinctly and e.g. have to approximate clients consumption spending at least to some extend. Moreover, we do not receive inter-day timestamps of the observed financial transactions, by which we e.g. could analyze whether clients actually inquire their accounts prior to transactions like credit card utilization or savings accounts transfers. Finally, our study focuses on financial attention and its association with financial decision-making. Mobile-banking applications offer, besides of account inquiry functionality, several further features that potentially improve clients financial management capabilities. Further research could contribute to literature by analyzing other mobile-banking features and their association with customers financial behavior.

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2.9 Appendices

2.9.1 Variable Definition

Variable	Definition
Channel Usage	
Mobile-Adoption (IV)	Indicator variable which equals 0 (1) before (after) mobile-banking adoption.
Online-Adoption (IV)	Indicator variable which equals 0 (1) before (after) online-banking adoption.
Mobile- and Online-Adoption (IV)	Indicator variable which equals 0 (1) before (after) the client adopted both mobile- and online-banking.
Inquiry Any (IV)	Indicator variable which equals 1, whether the client inquired her accounts through any channel during the observed day, and 0 otherwise.
Inquiry Mobile (IV)	Indicator variable which equals 1, whether the client inquired her accounts via mobile-banking during the observed day, and 0 otherwise.
Inquiry Online (IV)	Indicator variable which equals 1, whether the client inquired her accounts via online-banking during the observed day, and 0 otherwise.
Inquiry ATM (IV)	Indicator variable which equals 1, whether the client inquired her accounts via ATMs during the observed day, and 0 otherwise.
Indicator Variables	
Overdraft (IV)	Indicator variable which equals 1, whether the client faced overdraft at the end of the observed day, and 0 otherwise.
Salary Inflow (IV)	Indicator variable which equals 1, whether the client received salary inflows during the observed day, and 0 otherwise.
Money Inflow (ex Salary) (IV)	Indicator variable which equals 1, whether the client received any money inflow (without salary) during the observed day, and 0 otherwise.
Money Outflow (IV)	Indicator variable which equals 1, whether the client proceeded money outflows during the observed day, and 0 otherwise.
Credit Card available (IV)	Indicator variable which equals 1, whether the client possessed a credit card during the observed day, and 0 otherwise.
Credit Card Settlement (IV)	Indicator variable which equals 1, whether the client proceeded transactions that balanced credit card accounts during the observed day, and 0 otherwise.
Credit Card Payment (IV)	Indicator variable which equals 1, whether the client proceeded credit card payments during the observed day, and 0 otherwise.
Savings available (IV)	Indicator variable which equals 1, whether the client avails liquidity on savings accounts at the end of the observed day, and 0 otherwise.
Euro Variables	
Salary Inflow (Euro)	Sum of all salary inflows during the observed day (in euro).
Money Inflow (ex Salary) (Euro)	Sum of all money inflows (without salary) during the observed day (in euro).
Money Outflow (Euro)	Sum of all money outflows during the observed day (in euro).
Credit Card Limit (Euro)	End-of-day credit card limit (in euro).
Credit Card Settlement (Euro)	Sum of all transactions that balanced credit card accounts during the observed day (in euro).
Credit Card Payment (Euro)	Sum of all credit card payments during the observed day (in euro).
Salary Month (Euro)	Sum of all salary payments during the observed month (in euro).
Current Account Balance (Euro)	Sum of end-of-day balances in current accounts (in euro).
Savings Accounts Balance (Euro)	Sum of end-of-day balances in savings accounts (in euro).
Investments (Euro)	Sum of end-of-day balances in investment accounts (in euro).
Loans (Euro)	Sum of end-of-day balances in loan accounts (in euro).
Conditional Values	
Money Inflows (ex Salary) (Euro)	Sum of all money inflows (without salary) during the observed day conditional on receiving such inflows (in euro).
Money Outflows (Euro)	Sum of all money outflows during the observed day conditional on proceeding such outflows (in euro).
Credit Card Limit (Euro)	End-of-day credit card limit conditional on possessing a credit card (in euro).
Credit Card Payment (IV)	Indicator variable which equals 1, whether the client proceeded credit card payments conditional on possessing a credit card with available spending limit during the observed day, and 0 otherwise.
Credit Card Payment (Euro)	Sum of all credit card payments during the observed day conditional on proceeding such payments (in euro).
Demographics	
Male (IV)	Indicator variable which equals 1, if the customer is male, and 0 otherwise.
Age (Years)	Age of the customer (in years).

Table A-10: Definition of variables.

	Relative Portion
Sum of All Spendings	100.00%
Consumption	25.72%
Cash	24.67%
Financial Services	15.21%
Public and Private Associations	10.82%
Transfers between own Accounts	8.74%
Diverse	14.84%

Table A-11: Relative portions of spending categories. *Consumption* includes spending for consumption or service purposes, e.g. retailers, lifestyle, media usage, recreation, consulting, e-commerce and mobility. *Cash* contains cash transfers through branches and ATMs. *Financial Services* comprises spending for financial institutions like leasing or insurance companies. *Public and Private Associations* regards to money outflows like tax spending, donations or membership fees. *Diverse* sums up all other, mostly uncategorized spending.

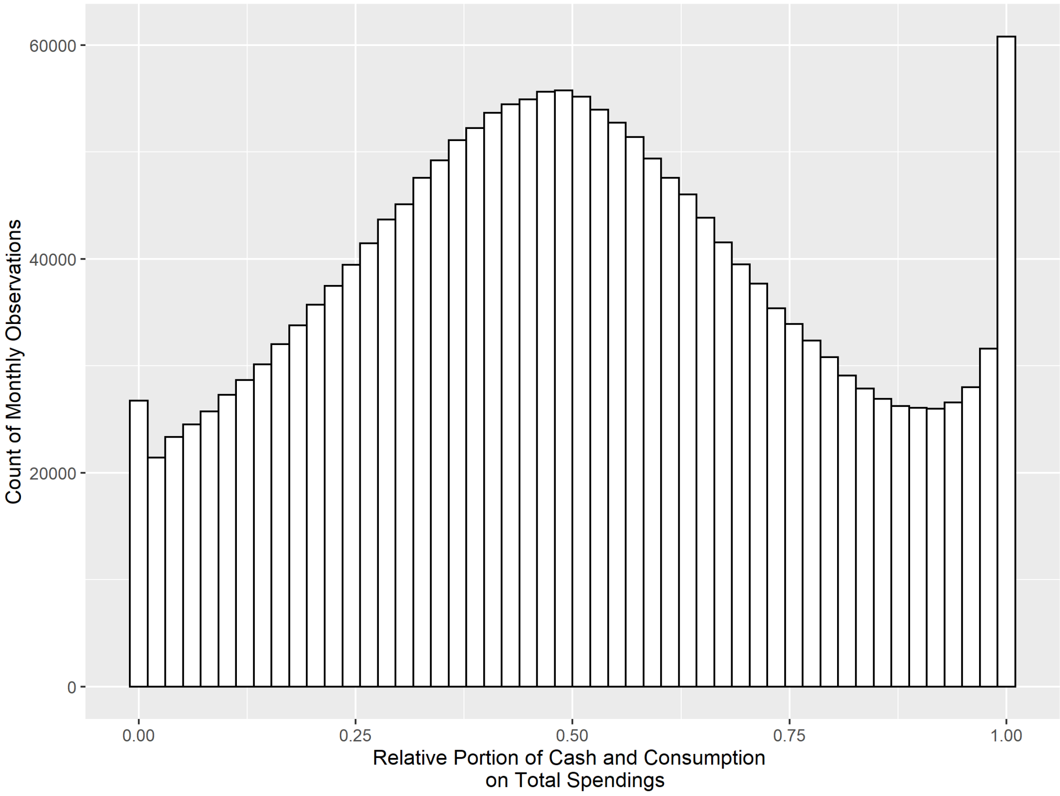

Figure A-7: Histogram of *cash&consumption* spending on all money outflows. X-axis gives the relative portion of *cash&consumption* on all money outflows, y-axis provides the count of monthly observations.

2.9.2 Calculation of Cash- & Consumption Spending

Our data provides information about daily money in- and outflows, but these spending are uncategorized. Fortunately, we receive monthly aggregated data about payment categories for each individual. Table A-11 informs about the overall spending behavior in our sample. As we want to discover changes in personal consumption behavior, we start by focussing on the *consumption*-category, which stands for 25.72% of all money outflows. These payments are initiated via debit cards or credit cards and can be categorized by the bank system. Furthermore, we have to consider that cash is mainly used at the point of sale of a merchant

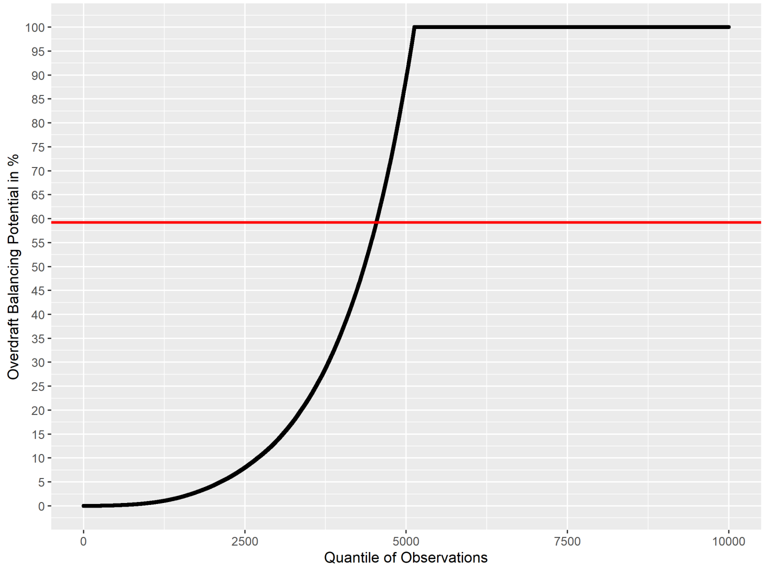

Figure A-8: Visualization of overdraft balancing potential. X-achsis groups the observations into 10,000 quantiles, y-achsis plots the proportion of overdraft that could be balanced by savings accounts transfers. The red line corresponds to the mean value of the y-achsis. Basis is the subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts.

(Wakamori and Welte, 2017). Hence, we denote that most cash payments, which stand for 24.67% of all money outflows in our data, are also used to fund personal consumption. As a result, we calculate the monthly sum of these two categories per customer and denote them as *cash&consumption*-spending, which are used to fund personal consumption.[12] Figure A-7 visualizes the distribution of *cash&consumption*-proportions among all observed individuals and shows differences between customers.[13] To take these differences into account, we use monthly *cash&consumption*-proportions of each individual and multiply daily spending in that particular month with the according *cash&consumption*-proportion. By this we are able to indicate daily *cash&consumption*-spending, which amount to 41.06€ on average.

2.9.3 Potential to balance overdraft by using liquidity from savings accounts

Basis for this Appendix is a subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts. Figure A-8 divides this subsample into 10,000 quantiles and visualizes the proportion of overdraft that could be balanced directly by transferring money from savings accounts. As shown by the red line, 59.69% of the overall overdraft amount could be balanced. Roughly 50% of all observations could compensate their overdraft completely. Although all customers in this subsample have been able to settle their overdrafted account at least partially, Figure A-9 unveils that only 3.28% of those observations availed this opportunity. This value splits up in 0.78%, who fully, and 2.50%, who partially balanced their overdraft.

12 For reasons of simplicity, we denote *cash&consumption*-spending as consumption spending in our paper and use *cash&consumption*-spending only in the Appendix.

13 We can also observe a peak at the lower and especially at the higher end of the distribution. Some accounts seem to be used as a budget account and are exclusively used to fund personal consumption (not at all). However, by performing fixed-effects regression in section 2.5.2, we calculate within individual effects and control for such special used current accounts.

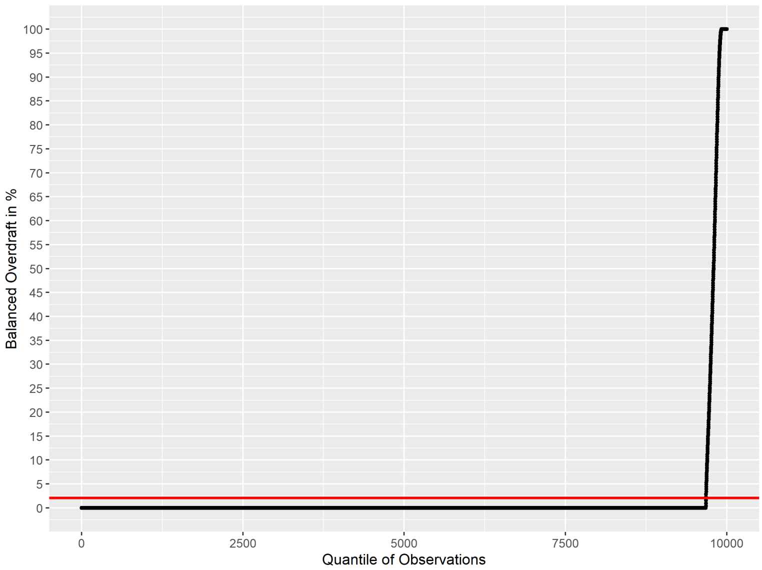

Figure A-9: Visualization of balanced overdraft. X-achsis groups the observations into 10,000 quantiles, y-achsis plots the proportion of overdraft balanced by savings accounts transfers. The red line corresponds to the mean value of the y-achsis. Basis is the subsample of 4,283,870 observations including all customers, who face an overdrafted current account while holding liquid assets in their savings accounts.

3 The Impact of Mobile-Banking Adoption on Retail Banking

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Technical Report, December 2020

Own Share: 60%

Abstract

In this paper we examine drivers of mobile-banking adoption as well as resulting changes in client's banking behavior. We find that customer's financial demands and digital skills correlate positively whereas age is associated negatively to mobile-banking adoption. We document a strong increase in online-banking transactions after mobile-banking adoption, while ATM, call center and branch transactions get substituted. Furthermore, mobile-banking adopters perform more digital money transfers and cashless payments while they reduce offline money transfers and cash payments. Finally, adopters acquire more products and active mobile-banking users increase their loyalty with the bank distinctly.

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3.1 Introduction

In this paper we empirically examine drivers of mobile-banking adoption and the resulting changes in client's banking behavior using large-scale individual-level panel data. Mobile-banking evolves to the state of the art channel for daily banking activities. In 2018 finance apps have been downloaded 3.4 billion times globally, which documents a massive increase by +75% compared to 2016. While Asia Pacific can be referred to as the global leader with respect to mobile-banking activities, North America and Europe are the second strongest areas. In those regions, finance app downloads doubled from 200 mio. in 2012 to 400 mio. in 2018 (Liftoff and Leanplum, 2019; Haslam, 2019). This change in customer behavior has the potential to transform retail banking fundamentally. About one in two 18-34 year old current account customer in France, Germany and the UK say they discover new retail banking options through their smartphone. They expect that managing money should be as easy as a simple tap or swipe. As a result, these customers disclose that an easy to navigate mobile app is an important consideration when deciding which new retail bank to sign up for (Facebook, 2019). This trend builds the ground for fintechs, which come up with new and disruptive business models to shake up the financial services industry (Lee and Shin, 2018).

Traditional omni-channel banks are forced to address these pervasive changes in how their clients claim to interact with them and therefore almost every bank offers a mobile-banking app today. But how radical are the economic effects of this mobile orientation of customers on banks? Is mobile-banking just a trendy gadget or does it fundamentally influence day-to-day financial behavior? Are customer's utilization of payment instruments, channel usage behavior or business intensity with the bank changing? And finally, is the goal of traditional banks to establish stable profits and high product penetration still achievable while dozens of financial services, which are accessible in the pocket of every customer, compete for a business relationship with the client?

Our paper uses large scale individual-level panel data from a German regional bank to address these research questions. We apply survival analysis (Cox, 1972) to investigate reasons for mobile-banking adoption and utilize difference-in-differences techniques to evaluate resulting changes in customer's banking behavior twelve months after adoption. Thereby, we contribute to the literature in four distinct dimensions. First, we characterize mobile-banking adopters, which is crucial for bank marketers to address their mobile-banking offer geared to the target group. Therefore, we build on studies, which analyze determinants of mobile-banking adoption (Jünger and Mietzner, 2019; Cope et al., 2013; Laukkanen and Cruz, 2012; Saeed, 2011; Koenig-Lewis et al., 2010; Luo et al., 2010; Laukkanen and Pasanen, 2008; Mattila, 2003). These survey-based studies are typically associated with major limitations, which lead to measurement errors (Xue et al., 2011). By using large scale panel data, we overcome these limitations and find that client's demand for financial services as well as her skills regarding the usage of digital (financial) services are attended to mobile-banking adoption. Furthermore, we investigate that especially younger people adopt this banking channel. Our findings conflict with prior survey-based literature by showing that, most recently, men and women adopt mobile-banking equally.

Second, we investigate changes in banking behavior, which builds the ground of the business relation between banks and customers. Therefore, we examine the impact of mobile-banking adoption on dimensions like channel and product usage as well as customer profitability. To this end, we build on Xue et al. (2011); Campbell and Frei (2010) and Xue et al. (2007), who investigate changes through online-banking adoption. We transfer their approach to mobile-banking adoption. With respect to customer's channel usage, we examine on one side a very strong augmentation effect on online-banking, where transactions more than double after mobile-banking adoption. On the other side, we observe substitution effects on ATMs, call center and branches, which arise in reductions of transactions by -25% to -65%, compared to the matched controls. Product usage, which is relative to the matched controls already higher before mobile-banking adoption, increases additionally. Furthermore, we observe a short-term decrease by roughly -28% in customer profitability compared to the matched controls. In the long-term instead, this effect vanishes and we do not find significant differences in profitability between mobile-banking adopters and non-adopters.

Third, we survey changes in customer's payment behavior. A more frequent utilization of digital finance tools in general as well as higher transparency about budgets in particular (Becker et al., 2021; Levi and Benartzi, 2020; Carlin et al., 2019a), which is one of the major causes of (still) using cash (Bartzsch et al., 2019; Kalckreuth et al., 2014), could lead to a drift from cash to cashless payment methods. Besides various macroeconomic reasons, this would be desirable for banks, as these cashless payments generate valuable data to provide individualized offers to their customers (Massi et al., 2019). This data becomes a crucial asset for banks to constitute proximity to customers in an increasingly digitized economy with shrinking personal interactions. We investigate that the number of total money transfers increases, which is driven by online- and mobile-banking transfers, while the number of offline transfers drop by roughly 50%. The usage of cash gets substituted by cashless payment methods, namely debit cards and credit cards.

Finally, we analyze the association of mobile-banking adoption with customer's loyalty. Previous research examining online-banking found an increase in customer's loyalty after adoption by encouraging them to interact more frequently with the bank (Xue et al., 2011; Campbell and Frei, 2010). This finding is further backed by results of studies investigating other omni-channel service industries, such as retailing. Soysal and Krishnamurthi (2016) examine how the adoption of the lower-quality, lower-price factory outlet channel impacts customer's spending in a retailer's higher-quality, higher-price traditional retail store channel and find an increase in sales in the traditional distribution channel. The adoption of mobile-banking, which typically stands for banking activities on a smaller screen with restricted features compared to online-banking, leads to related research questions. We find a significant reduction of -34.4% in churn rate for those customers, who adopt and actively use mobile-banking.

Moreover, our findings are potentially useful for practitioners. Our adoption analysis enables bank marketers to address their mobile-banking offer, geared to the target group. Furthermore, our post-adoption analysis reveals relevant insights for bank managers as well. On the basis of our results managers are able to anticipate changes in omni-channel usage and payment behavior to offer adequate and cost-effective omni-channel banking services. Furthermore, bank managers need insights whether mobile-banking strengthens the relationship to their customers or reduces business intensity and accelerating customer churn (e.g. to a fully digital fintech), once they get used to the amenities of digital banking. On the basis of the observed outcomes banks should encourage customers to adopt as well as actively use mobile-banking.

The remainder of the paper proceeds as follows. Section 3.2 characterizes the retail banking market in Germany. Section 3.3 reviews related literature and derives expectations about our adoption and postadoption analysis. We outline characteristics of our data in section 3.4. Section 3.5 introduces our empirical strategy and section 3.6 presents our findings. We discuss the results and conclude the paper in section 3.7.

3.2 Institutional Setting

The German retail banking market can be characterized as a highly developed polypoly. There exist three important groups, which build the 'three-pillar-banking-system', differ considerably in terms of their structure and compete for market share since roughly 200 years. Pillar one is made up of private credit institutions, both according to their legal forms as well as their ownership structures. In terms of total assets, pillar one makes up about 40 percent of the entire German banking system. Pillar two is denoted as the savings banks group. In terms of aggregate total assets, the entire savings banks group is about as large as the group of the private credit institutions. Pillar three is made up by the cooperative banking group. It comprises a larger number of independent institutions than the other two groups, whereas in terms of total assets it is only about half the size of the two other pillars (Behr and Schmidt, 2015).

Compared to global peer markets, long-term profitability is low and German banks struggle to earn their cost of capital. Major reasons for this situation are the highly competitive market, a strong dependency on net interest income with comparative low prices for banking products and services in combination with a rigid cost base, driven by high branch density and a large staff base (Koch et al., 2016).

Dimension	2015	2018	Percentage Change
Population (thousands)	81,687	82,902	+1.5%
Number of financial institutions	1,774	1,584	-10.7%
thereof private credit institutions	276	263	-4.7%
thereof savings banks	425	399	-6.1%
thereof cooperative banks	1,049	917	-12.6%
thereof others	24	5	-79.2%
Number of local bank branches	34,115	27,993	-17.9%
Number of ATMs	86,702	85,885	-0.9%
Share of households with a PC	87%	90%	+3.4%
Share of households with a mobile phone	94%	97%	+3.2%
Share of households with internet access	79%	93%	+17.7%
Share of households with online-banking	52%	59%	+13.5%

Table B-1: Key dimensions explaining the German retail banking market. Column 2 documents values out of year 2015, column 3 values out of year 2018 and column 5 prints the percentage change from 2015 to 2018. Row 4 and 5 sum up values of the savings and cooperative banks as well as their related institutions like *Landesbanken*. The values for households with internet access also include mobile internet access (smartphone, surf sticks etc.). The values in column 2 and 3 are obtained from Deutsche Bundesbank (2019b); Statistisches Bundesamt (2019) and Statistisches Bundesamt (2015).

Table B-1 documents some key figures, which characterize the German banking system. As the overall population grew from 2015 to 2018 by +1.5%, the number of banks diminished by -10.7%, which is one result of the highly competitive situation in the German banking system. Even though consolidation takes place, the market is still fragmented with more than 1,500 banks competing for the customers. Furthermore, the asset concentration is still lower than in peer markets: the top five banks account for only 44 percent of total domestic banking assets. In the US, the concentration amounts to 56 percent, in the UK it is 84 percent and in other Western European countries it averages at 76 percent (Koch et al., 2016).

Moreover, Table B-1 outlines that German citizens are prepared to behave increasingly digital. In 2018 almost every household possesses a mobile phone (97%) and most of them a personal computer (PC) (90%). Furthermore, the number of households with internet access (online-banking) increased by +17.7% (+13.5%) from 2015 to 2018, respectively. In the same time banks diminished their local branch network by -17.9% to account for changes in customer demand as well as price pressure in the market. These values show up a highly dynamic banking system, which is among others strongly influenced by digitization. Koch et al. (2016) outline the low-interest-rate environment, regulatory tightening and digitization as the most relevant environmental factors for German banks and denote the digitization strategy as an key enabler for banks. Hence, Germany comes up as a promising area for our research regarding mobile-banking adoption and resulting changes in client's banking behavior.

3.3 Literature Review and Hypotheses

Research on mobile-banking adoption as well as postadoption changes is situated in an early stage. One can find a couple of studies that use survey data to detect drivers of mobile-banking adoption (Jünger and Mietzner, 2019; Cope et al., 2013; Laukkanen and Cruz, 2012; Saeed, 2011; Koenig-Lewis et al., 2010; Luo et al., 2010; Laukkanen and Pasanen, 2008; Mattila, 2003). As outlined by Xue et al. (2011), survey-based studies typically face two major limitations: On the one hand, they derive their results from cross-sectional data and are not able to consider changes over time. On the other hand, surveys could be biased, as they rely on self-reported data rather than actual observation, which leads to measurement errors. Only Carlin et al. (2019a) as well as Levi and Benartzi (2020) incorporate transaction data from FinTechs in order to overcome these limitations. Both find an increase in login frequency, which comes along with reduction in high-interest unsecured debt and bank fees (Carlin et al., 2019a) as well as a cut in discretionary spending (Levi and Benartzi, 2020). To the best of our knowledge, there is no approach that utilizes time series transaction data from a bank as opposed to a fintech to identify drivers of mobile-banking adoption as well as related postadoption changes. Contrary to fintechs, which regularly limit their offering to improve the service of selected financial needs, banks offer holistic financial services to their clients and cover a wide range of financial demands. By incorporating transaction data from a bank, we are able to investigate comprehensive insights regarding the impact of mobile-banking on financial behavior. Subsequently, we derive relevant factors of our research dimensions as well as our hypotheses on the basis of related literature. As mobile-banking studies are rare, we also focus on studies examining online-banking, which can be denoted as another popular digital banking channel.

3.3.1 Reasons for Mobile-Banking Adoption (Adoption-Analysis)

Rogers (1983), Davis and Davis (1989) as well as Venkatesh et al. (2003) frequently build the theoretic background of studies which examine the adoption of new technologies.[1] They agree that technology adoption is inter alia influenced by the client's perception on how advantageous a new technology meets her actual needs. Furthermore, they have in common that the required effort to employ a new technology, which is among others influenced by prior experiences, is also a major factor in the adoption process. As a consequence, we expect that customer's demand for financial services as well as her skills regarding the usage of digital services impact mobile-banking adoption. This assumption is in line with findings of prior literature, which examine the utilization of digital banking channels and unveils that those two dimensions significantly influence the adoption process of the client. For instance Lee and Lee (2001) investigate that the use of other banking channels reflects customer demand for financial services, denote this as a need-based dimension in technology adoption and show that it is correlated positively with online-

1 *Diffusion of Innovation Model (IDT) of Rogers (1983); Technology Acceptance Model (TAM)* of Davis and Davis (1989); *Unified Theory of User Acceptance of Technology (UTAUT)* of Venkatesh et al. (2003)

banking adoption. Additionally, they declare that prior experiences of the consumer, e.g. utilization of digital services, accelerates the future adoption of similar technologies and denote this as a skill-based dimension. They show that both dimensions (need- and skill-based) correlate with the adoption decision substantially. On the basis of these theoretic assumptions in combination with empirical findings, we expect an association of customer needs and skills with mobile-banking adoption and include the following instruments into our adoption analysis.

Customer needs. Additional to Lee and Lee (2001), Xue et al. (2011) hypothesize that consumers differ in their demand for banking services. They instrumentalize a variable service demand, measured as transaction count across all channels for all deposit accounts with the bank, and investigate that customers with higher service demand adopt online-banking faster. Moreover, information about customer's business intensity with the bank, measured by product usage and customer profitability, come up as further promising instruments to measure customer's demand for financial services. While this approach is new in a mobile-banking adoption analysis, those dimensions are established in explaining online-banking adoption: Gensler et al. (2012); Berger and Gensler (2007) as well as Hitt and Frei (2002) show a positive correlation between product usage and online-banking adoption. Furthermore, Campbell and Frei (2010) as well as Hitt and Frei (2002) postulate that especially high profitable customers are more likely to use online-banking. This is in line with our above expectations, as higher product usage, which is also associated with increased customer profitability, implies a stronger demand for financial services. Hence, we derive the following hypotheses:

> **Hypothesis 1A (H1A):** *Higher transaction count in other banking channels is associated with faster mobile-banking adoption.*
>
> **Hypothesis 1B (H1B):** *Higher product usage is associated with faster mobile-banking adoption.*
>
> **Hypothesis 1C (H1C):** *Higher customer profitability is associated with faster mobile-banking adoption.*

Customer skills. By observing customer's channel usage and payment behavior, we receive indications about digital skills in financial behavior. Several studies unveil a positive correlation of ATM usage, which is a major self-service channel in retail banking, and online-banking adoption (Albesa, 2007; Curran and Meuter, 2005; Devlin and Yeung, 2003). Following Lee and Lee (2001), we also expect that higher transaction count in online-banking, which is one of the most popular digital banking channels, is associated with faster mobile-banking adoption. Additionally, we observe whether the client proceeds money transfers via offline channels or online-banking and receive another indicator about her digital skills in financial management. Finally, a growth in usage of credit cards after mobile-banking (Carlin et al., 2019a) or online-banking adoption (Berger and Gensler, 2007) is documented by prior research. Hence, we anticipate a coherence between self-service utilization in general and online-banking usage in particular as well as utilization of cashless payment methods, which represent a digitization in payment behavior, and mobile-banking adoption.

Hypothesis 2A (H2A): *Stronger usage of ATMs is associated positively with mobile-banking adoption.*

Hypothesis 2B (H2B): *Stronger usage of online-banking is associated positively with mobile-banking adoption.*

Hypothesis 2C (H2C): *Higher count in online money transfers is associated with faster mobile-banking adoption.*

Hypothesis 2D (H2D): *Stronger usage of cashless payment methods, namely debitcards and credit-cards, is associated positively with mobile-banking adoption.*

Customer demographics. Expectations and beliefs on the usefulness of new technology as well as behavior in information processing and decision making differ in age and gender (Ladhari and Leclerc, 2013; Venkatesh et al., 2003). Hence, we expect that these two dimensions are related to mobile-banking adoption, as well. Preliminary findings on the drivers of mobile-banking adoption show that age is an important feature and is associated negatively (Carlin et al., 2019a,b; Cope et al., 2013; Laukkanen and Pasanen, 2008; Mattila, 2003). Literature examining the adoption of electronic banking technologies in general (Lee and Lee, 2000) as well as online-banking in particular (Gensler et al., 2012; Lambrecht et al., 2011; Xue et al., 2011; Campbell and Frei, 2010; Berger and Gensler, 2007; Xue et al., 2007; Flavian et al., 2006; Devlin and Yeung, 2003; Hitt and Frei, 2002) also attest that younger people are more likely to adopt online-banking. Furthermore, several studies agree that men are more likely to use mobile-banking than women (Carlin et al., 2019a; Laukkanen and Cruz, 2012; Koenig-Lewis et al., 2010; Laukkanen and Pasanen, 2008; Mattila, 2003). These insights are, again, in line with online-banking studies, which document higher adoption rates of male customers (Lambrecht et al., 2011; Flavian et al., 2006; Devlin and Yeung, 2003). Hence, we derive two hypotheses on the coherence of customer demographics and mobile-banking adoption:

Hypothesis 3A (H3A): *Customer's age is associated negatively with mobile-banking adoption.*

Hypothesis 3B (H3B): *Male customer's are more likely to adopt mobile-banking than females.*

Controls. Finally, we control for customer's wealth status, measured by salary and balances on current, deposit, loan and investment accounts. Carlin et al. (2019a) report univariate statistics of mobile-banking adopters and outline that these have slightly higher income and account balances available. This insight is in line with Berger and Gensler (2007); Xue et al. (2007); Flavian et al. (2006) and Pikkarainen et al. (2004), who report higher income, Campbell and Frei (2010), who detect higher account balances and Devlin and Yeung (2003) as well as Hitt and Frei (2002), who include income and account balances and determine a positive correlation with online-banking adoption. Hence, we expect a positive coherence of wealth status controls and mobile-banking adoption.

3.3.2 Changes after Mobile-Banking Adoption (Postadoption-Analysis)

Our second object of investigation concerns the examination of possible changes after mobile-banking adoption. Whether and how mobile-banking generates additional value, especially from a banks perspective, is heavily dependent on possible changes in client behavior after its adoption (Xue et al., 2011). A change in customer behavior is likely for several reasons. Chase (1981) illustrates that the customer contact approach is a major aspect in the service industry. This approach holds that a service system's potential operating efficiency is a function of the degree to which the customer is in direct contact with the service facility relative to total service creation time for that customer:

$$\text{Potential facility efficiency} = f\left\{1 - \frac{\text{customer contact time}}{\text{service creation time}}\right\} \tag{1}$$

Chase (1978) declares that the less direct contact the customer has with the service system, the greater the potential of the system to operate at peak efficiency. Mobile-banking offers anytime and anywhere contact to the bank. Clients do not have to travel to a branch, consider opening times, be on hold in the call center or boot up a PC in order to utilize online-banking anymore. Mobile-banking services are typically highly available, quick and easy to use. Hence, customer contact time, which is required to fulfill a certain financial need, declines distinctly. Therefore, mobile-banking is probably associated with increased potential facility efficiency and should lead to changes in service consumption of the customer. This perception is in line with prior literature studying online-banking, which finds several changes in client's service consumption after adoption. Hence, we expect changes in customer's behavior along several dimensions.

Channel usage Prior literature finds that users increase their transactions with the bank after online-banking adoption. Xue et al. (2011); Campbell and Frei (2010) and Xue et al. (2007) document augmentation effects of online-banking adoption on transactions through all other banking channels. However, these results conflict with Xu et al. (2017), who examine the impact of the introduction of an tablet app on the pc and smartphone usage in an e-commerce setting. They find both augmentation effects on smartphone-sales and substitution effects on pc-sales after adoption of the tablet app. We transfer these approaches to mobile-banking and explore postadoption changes in the usage of the banks omni-channel offering, which is crucial for service provision but simultaneously a major cost pool in retail banking. As prior literature finds variation in client's usage of other channels after the adoption a new channel, we expect:

Hypothesis 4 (H4): *Mobile-banking adoption is associated with altered transaction counts in other channels.*

Payment behavior. Payment behavior of customer's in Germany is changing. The payments statistics of Deutsche Bundesbank, which we provide in Appendix 3.9.1, shows that offline and cash-related transfers diminish while digital[2] and cashless transfers become more popular over time. A higher potential facility efficiency, which is generated by mobile-banking adoption, is likely to accelerate this shift in behavior. Especially in Germany a high usage of cash is still observable (Jünger and Mietzner, 2019; Massi et al., 2019). This situation is adverse for various reasons: Cash is correlated to tax evasion and crime (Massi et al., 2019; Deutsche Bundesbank, 2018; Judson, 2017) and costs relative to sales volume are higher for cash compared to debitcard payments (Deutsche Bundesbank, 2019a). A stronger utilization of cashless payment methods instead would be advantageous, as these generate economic growth (Massi et al., 2019; Tee and Ong, 2016) as well as valuable data for banks to provide individualized offers to their customers (Massi et al., 2019). A major reason for the popularity of cash is the high transparency of budgets (Bartzsch et al., 2019; Kalckreuth et al., 2014). People have a look in their wallet to check how much money is left and whether or not budgets are exceeded. This demand for transparency about budgets is alternatively satisfied by mobile-banking. Jünger and Mietzner (2019) find that an increase in financial transparency is a major reason for people to adopt mobile-banking. Becker et al. (2021); Levi and Benartzi (2020) as well as Carlin et al. (2019a) detect a significant increase in account inquiries through mobile-banking, which also indicates an improvement in financial transparency. As people achieve higher financial transparency through mobile-banking, we expect a reduction in the usage of cash as well as a surge in the usage of cashless payments and postulate the following hypotheses:

Hypothesis 5A (H5A): *Mobile-banking adoption is associated with an increase in digital money transfers.*

Hypothesis 5B (H5B): *Mobile-banking adoption is associated with a decrease in offline money transfers.*

2 We denote money transfers, which are generated via digital channels like online- or mobile-banking, as digital transfers.

Hypothesis 5C (H5C): *Mobile-banking adoption is associated with a decrease in the utilization of cash.*

Hypothesis 5D (H5D): *Mobile-banking adoption is associated with an increase in the utilization of cashless payment methods.*

Product usage, customer profitability and churn. The final aspect of our postadoption analysis observes potential correlates of mobile-banking adoption with product usage, customer profitability and churn. Xue et al. (2011) find that online-banking adoption is linked to acquisition of additional products. Together with Campbell and Frei (2010), they also document a short-term decrease in customer profitability. This could be caused by enhanced money management capabilities of the customer, which short dated overcompensate the profitability surplus of increased product utilization.[3] Moreover, we investigate the association of mobile-banking adoption with customer's loyalty. Xue et al. (2011) as well as Campbell and Frei (2010) show that online-banking adoption leads to higher customer loyalty. Additionally, Chen and Hitt (2002) unveil that customer's usage frequency of online-services is important for their retention. These findings are further backed by results of studies investigating other omni-channel service industries, such as retailing. Soysal and Krishnamurthi (2016) find an increase in sales in the traditional distribution channel after the customer adopts the lower-quality, lower-price factory outlet channel. We transfer these findings to mobile-banking, which often offers only restricted and very basic financial services compared to other banking channels. Prior research indicates a positive association of mobile-banking adoption with customer loyalty. In contrast, customers could churn to an essentially digital fintech, which usually offers more comprehensive mobile-banking functionality, once they get used to the amenities of digital banking. Based on prior literature we derive our final hypothesis:

Hypothesis 6A (H6A): *Mobile-banking adoption is associated with an increase in product usage.*

Hypothesis 6B (H6B): *Mobile-banking adoption is associated with a short-term decrease in customer profitability.*

Hypothesis 6C (H6C): *Mobile-banking adoption is associated with a decrease in customer churn rate.*

3.4 Data

We analyze large scale individual-level panel data from a German cooperative bank. This bank is locally owned and, similar to other savings and cooperative banks in Germany, tends to attract traditional bank customers with a preference for a strong and long-lasting relationship with their house bank. Our bank offers a wide range of financial services, such as current accounts, deposit accounts, securities accounts and

3 Enhanced money management capabilities, among others, lead to higher (lower) rates of interest to be paid on interest (loan) accounts (Campbell and Frei, 2010).

loans (including mortgages), to its retail customers. The bank serves over 250,000 individual customers. Those customers can use the banks branch and ATM network, call center, online- and mobile-banking to proceed their banking activities. The bank operates over 50 branches and more than 100 ATMs, with at least one branch and ATM in every district of the operating area. The call center is available from Monday to Friday from 7 a.m. to 8 p.m. ATMs, online- and mobile banking are accessible 24 hours on 7 days a week.

We receive data for a 48 month period from January 2015 to December 2018. The data provides information about demographic characteristics, account balances, payment transactions, channel usage and business intensity of the customers. All data are derived from the banks operational system and are therefore complete as well as highly accurate. We focus on adult private customers, who are no employees of the bank. Some customers might hold accounts at multiple banks and we aim to explore only primary used bank accounts. Therefore, we retain only those customers, who possess a current account in every month of our investigation period and receive salary or pension payments in at least two-thirds of all months. After applying these restrictions, we continue with 88,342 customers. Since we aim to analyze covariates for mobile banking adoption as well as changes in banking behavior after adoption, we exclude customers, who have already used mobile-banking in January 2015 or before and result in a final sample of 62,100 customers (2,549,877 monthly observations), 8,900 of whom adopted mobile-banking during our period under review.

Table B-2 provides summary statistics of our sample. A definition of all variables is provided in the Appendix 3.9.2. The statistics of demographics and business intensity are based on the full sample. The categories channel usage, payment behavior and wealth status provide descriptive statistics after customers first usage of the respective channel, payment method or product category. Thus, we remove observations of those customers, who do not use the respective channel, payment method or product category, in order to reduce skewness of our descriptive results. A detailed overview of the types of transactions per channel is provided in the Appendix 3.9.3. The average customer is 54 years old. The gender of the sample is almost balanced with slightly more female customers. We incorporate data about the business intensity, which the customer maintains with the bank, and observe that the average customer uses 3.16 different products,[4] generates a monthly gross margin of 23.62 euro (measured by the banks internal control system) and has a business relation of 205.17 months (roughly 17 years) with the bank.

Conditional on using the respective channel, payment method or product type, the average customer performs 31.07 online-banking, 6.43 ATM, 1.97 call-center and 1.27 branch transactions per month. The subsample-sizes show that almost all clients use ATMs and branches, while online-banking and call-

4 Product usage measures, how many of the following distinct product categories are used: current, loan, deposit or custody account, credit card, share in the company/bank, savings at a building society, insurance.

center are used more seldom. As we exclude those customers, who have already used mobile-banking in January 2015 or before (see above), it is likely that many online-banking users are excluded, too. However, the call-center still seems to be used rarely. Furthermore, the average customer performs 1.32 offline and 2.64 online transfers, 2.91 cash withdrawals and 0.32 cash deposits (by branch and/or ATM), 4.61 debitcard and 0.61 credit card payments per month, conditional on using the respective payment method. The subsample-sizes unveil that most customers use offline transfers, cash withdrawals and debitcard payments at least to some extent. However, online transfers, cash deposits and credit card payments are performed more seldom. Once more, the low N in our observation of online transfers results at least to some extent out of our exclusion strategy of prior mobile-banking adopters. Finally, we observe customer's wealth status. The average customer earns a monthly salary of 1,551 euro and holds 11,693 euro in her current account, 8,601 euro in her deposit account, 32,059 euro in investments (capital market products like shares, bonds, mutual funds etc.) as well as 11,593 euro in loan accounts, conditional on receiving salary or using the respective product type. Because of our exclusions strategy documented above, all observations represent a client with a current account and most of them receive salary payments. Furthermore, most of the observed customers possess a deposit account at our research site. However, the subsamples of customers owing an investment or loan account amount to roughly 20% and 40% of the full sample, respectively.

Depending on the object of investigation, the number of analyzed individuals changes. The full sample, as derived above, contains 62,100 customers with 8,900 mobile-banking adopters. For the adoption as well as our difference-in-differences post-adoption analysis we need to focus on those 7,810 customers, who we can observe at least one month before adoption. The final aspect of our post-adoption analysis concerns the impact of mobile-banking adoption on customer's 12-month churn rate. For this final research dimension we further restrict the observed mobile-banking adopters on those 7,312 clients, who adopt before January 2018 and are therefore observable at least 12 months after their adoption.

Statistic	Unit of Measurement	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Demographics							
Age	Years	2,549,877	53.917	20.721	35.750	54.750	70.833
Male	Indicator Variable	2,549,877	0.440	0.496	0	0	1
Business Intensity							
Product usage	Number of distinct products	2,549,877	3.160	1.425	2	3	4
Customer profitability	Euro	2,549,877	23.621	124.963	5.620	10.540	20.610
Tenure	Months	2,549,877	205.174	99.970	149	192	283
Channel Usage (Subsample)							
Online-Banking	Number of transactions	669,477	31.068	52.608	3.000	16.000	40.000
ATM	Number of transactions	2,474,099	6.426	6.869	2.000	5.000	9.000
Call Center	Number of transactions	186,479	1.969	5.993	0.000	0.000	0.000
Branch	Number of transactions	2,049,070	1.269	2.185	0.000	0.000	2.000
Payment Behaviour (Subsample)							
Offline transfers	Number of transfers	1,748,709	1.318	2.267	0.000	0.000	2.000
Online transfers	Number of transfers	454,258	2.642	4.253	0.000	2.000	4.000
Cash withdrawals	Number of withdrawals	2,437,480	2.912	3.046	1.000	2.000	4.000
Cash deposits	Number of deposits	1,215,795	0.319	0.806	0.000	0.000	0.000
Debitcard payments	Number of payments	1,954,707	4.605	5.835	0.000	3.000	7.000
Credit Card payments	Number of payments	343,648	0.605	0.521	0.000	1.000	1.000
Wealth Status (Subsample)							
Salary	Euro	2,516,255	1,551.332	2,856.964	792.830	1,361.890	1,990.030
Balance of Currents	Euro	2,549,877	11,693.020	148,286.000	821.240	2,307.730	7,965.915
Balance of Deposits	Euro	2,109,645	8,601.095	31,268.040	50.000	375.000	3,833.750
Balance of Investments	Euro	501,444	32,058.700	196,271.000	2,110.765	8,696.805	26,429.470
Balance of Loans	Euro	1,031,218	11,593.340	63,087.390	0.000	100.000	2,586.472
Number of Individuals							
Full Sample	62,100						
MB Adopters	8,900						
MB Adopters for (Post-)Adoption Analysis	7,810						
MB Adopters for 12m Churn	7,312						

Table B-2: Univariate description of the variables. The statistics of demographics and business intensity are based on the full sample of 62,010 customers with up to 48 end of month observations per individual (January 2015 to December 2018). The categories channel usage, payment behavior and wealth status provide descriptive statistics after customers first usage of the respective channel, payment method or product type. Thus, we remove observations of those customers, who do not use the respective channel, payment method or product type, respectively, in order to reduce skewness of our descriptive results. Minimum and maximum values are suppressed for reasons of data privacy. A definition of all variables is provided in Appendix 3.9.2, a detailed overview of the types of transactions per channel is provided in Appendix 3.9.3.

3.5 Empirical Strategy

3.5.1 Adoption Analysis

In order to explore characteristics of mobile-banking adopters, we perform survival analysis and use the Cox Proportional Hazard Model (CoxPH), which is used frequently in observational studies with time-to-event data. (Cox, 1972; Fisher and Lin, 1999; Lu, 2005)

Suppose we observe I Individuals $i = 1, ..., I$, at different time periods T, with $t = 1, ..., T$. We obtain a vector X_{ti} of time-varying covariates of individual i at time t. The CoxPH relates these parameters to the baseline hazard function $\lambda_0(t)$ for the standard set of conditions $X = 0$ in the following functional form (Cox, 1972):

$$\lambda(t, X_i) = \lambda_0(t) exp\{\beta^T X_{ti}\} \tag{2}$$

In our study $\lambda(t, X_i)$ denotes the probability of i, who is observed at the end of month t, to adopt mobile-banking, measured by a first login in the mobile-banking app, in the following month $t + 1$. By this means we analyse those 7,810 customer, who we can observe at least one month before adoption. As derived in section 3.3.1, we include information about customer's demographics, channel usage, payment behavior and business intensity as covariates X into our model. Additionally, we control for the log of customer's account balances and salary payments, divided into terciles.[5]

The CoxPH makes two crucial assumptions: First, the exponentiated covariates X are assumed to be linear predictors of $\lambda(t, X_i)$. Second, the effect of a covariate does not change over time (so called *proportional hazard assumption (pha)*). Therefore, all β are assumed to be constant for all t. This assumption applies even in our panel-data setting: Even though values may change over time, the effect of each covariate is assumed to be constant (Grant et al., 2014). In order to satisfy the *pha*, we build strata for every year of our observation. As a consequence, we receive distinct β for every year and each β has to be constant for all t of that particular year. Subsequently, these β can be used to examine whether or not effects change over time. After estimation of the CoxPH, we follow May and Hosmer (1998) to validate the goodness-of-fit as well as the linearity assumption and Grambsch and Therneau (1994) to monitor the *pha* of our model. We receive reasonable results for these tests, which are additionally approved by highly significant likelihood ratio, Wald and score tests.

5 We build terciles of salary payments and denote individuals as a low-, medium- or high-income customer on the basis of this terciles.

3.5.2 Postadoption Analysis

3.5.2.1 Risk Set Matching

In studies that analyze both time-dependent covariates with a time-dependent treatment event, researches have to balance the distribution of the covariates at every time point (Lu, 2005). We perform risk set matching, in which a treated client is matched to a not-yet-treated client,[6] who has exhibited similar time-dependent covariates up to the moment when the treatment occurs, by using the hazard component $exp\{\beta^T X_{ti}\}$ of equation (1) as a time-dependent propensity score (Lu, 2005; Rosenbaum, 2010). This procedure computes a distance score between a treated unit and all possible untreated neighbors, based on our time-dependent propensity score. As suggested by Abadie and Imbens (2006) and similar to Xue et al. (2011), we match each treated unit with the three closest untreated neighbors. We perform matching with replacement and therefore every untreated customer can be used multiple times as a matching partner. We enforce exact matching on month of adoption and an indicator variable, whether or not the customer already uses online banking.

In order to check whether or not the sample is balanced reasonably, we use the standardized bias (SB) across covariates, which is a commonly used measure to assess balance after matching. An SB of less than 0.25 can be seen as a moderate rule of thumb for a reasonable matching. If researchers want to use a stricter performance measure, a SB of less than 0.1 should be preferred (Harder et al., 2010). Figure B-4 in Appendix 3.9.4 visualizes our matching results and shows that all variables achieve an SB below 0.10. Therefore, we denote all variables as reasonable balanced.

3.5.2.2 Difference-in-Differences Estimation

In the vein of Xu et al. (2017), we perform the following difference-in-differences regression using our matched sample:

$$Y_{it} = \alpha_t + \beta_1 TREAT_i + \beta_2 POST_{it} + \beta_3 TREAT_i \cdot POST_{it} + \epsilon_{it}, \tag{3}$$

where Y denotes the dependent variable of interest. α_t controls for month-level fixed effects. $TREAT$ is an indicator variable, which equals 1 (0) for every mobile-banking adopter (non-adopter) and controls for potential time-invariant differences between both groups. $POST$ is also an indicator variable, which equals 1 (0) for every observation after (before) mobile-banking adoption and accounts for potential temporal effects that may also influence Y. Matched controls receive similar values as their associated treatment clients for this binary variable. β_3 denotes our difference-in-differences (DiD) estimate. Standard errors are clustered at the level of matched pairs.

6 As a consequence, it is possible that a client is used as a control-unit during those points in time, where she has not received the treatment. If she receives the treatment afterwards, she will be used as a treated customer.

	Year 2015		Year 2016		Year 2017		Year 2018	
	Coefficient	in %	Coefficient	in %	Coefficient	in %	Coefficient	in %
Channel Usage								
Online-Banking Tx	0.0042***	0.4%	0.0031***	0.3%	0.003***	0.3%	0.0019***	0.2%
ATM Tx	−0.0093	−0.9%	−0.012	−1.2%	0.0071	0.7%	0.0131*	1.3%
Call Center Tx	0.0011	0.1%	0.009	0.9%	0.0312***	3.2%	0.0339***	3.4%
Branch Tx	0.0477	4.9%	−0.0024	−0.2%	0.0851***	8.9%	0.0549**	5.6%
Business Intensity								
Product Usage	0.1444***	15.5%	0.0928**	9.7%	0.0963***	10.1%	0.0653**	6.7%
Customer Profitability	0.0001	0.0%	0.0003**	0.0%	0.0002	0.0%	0.0001	0.0%
Payment Behaviour								
Offline Transfers	0.0176	1.8%	−0.0305	−3.0%	−0.0796***	−7.7%	−0.0464*	−4.5%
Online Transfers	0.0415***	4.2%	0.026**	2.6%	0.0174**	1.8%	0.0024	0.2%
Cash Withdrawals	−0.0027	−0.3%	−0.013	−1.3%	−0.0404***	−4.0%	−0.0517***	−5.0%
Cash Deposits	0.117**	12.4%	0.1313***	14.0%	0.0961***	10.1%	0.0721*	7.5%
Debitcard Payments	0.0237***	2.4%	0.018***	1.8%	0.015***	1.5%	0.0148***	1.5%
Credit Card Payments	0.1478	15.9%	0.3076**	36.0%	0.2259**	25.3%	0.2378**	26.8%
Demographics								
Age	−0.0773***	−7.4%	−0.0768	−7.4%	−0.0709***	−6.8%	−0.0722***	−7.0%
Male	0.2284***	25.7%	0.0292	3.0%	0.0912*	9.5%	0.0259	2.6%
Controls	Yes		Yes		Yes		Yes	
Observsations	2,319,456							
Observed Adoptions	7,810							
Likelihood Ratio Test	13,858 on 80 df, p = < 0.0001							
Wald Test	9,165 on 80 df, p = < 0.0001							
Score (logrank) Test	13,925 on 80 df, p = < 0.0001							

Table B-3: Results of the Cox Proportional Hazard Model, which investigates drivers of mobile-banking adoption. The results are based on a sample of 62,100 individuals with 2,319,456 monthly observations, in which 7,810 individuals adopt mobile-banking. Column 1 prints the variable of interest. Columns 2, 4, 6 and 8 document the β-coefficients of regression 2 for the years 2015 to 2018, respectively. We receive these annual values, as we build strata for every year in our observation period in order to conform to the proportional hazard assumption (pha). Columns 3, 5, 7 and 9 provide the percentage change in annual adoption probability, which result from an increase in the covariate by one unit, holding all other coefficients constant. We receive these values through exponentiation of the CoxPH coefficient.

On the basis of this regression setup, we calculate 3-month, 6-month, 9-month and 12-month DiD for our balanced matched sample. By performing DiD, we control for self-selection and time-series heterogeneity, simultaneously. We explore changes in customer's channel usage, payment behavior as well as business intensity and churn. In order to investigate the association of mobile-banking adoption with customer's 12-month churn rate, we introduce a churn-indicator variable, which equals to 1, if the customer left the bank, and zero otherwise.[7] Subsequently, we calculate 12-month DiD for our churn-indicator variable.

3.6 Results

3.6.1 Adoption Analysis

Table B-3 shows results of the CoxPH. Since we calculate strata for year of observation, we receive regression coefficients for every particular year, which can be compared in detail. Every column of Table B-3 provides annual CoxPH coefficients and the percentage change in adoption probability, which results from an increase in the covariate by one unit, holding all other coefficients constant.

7 We declare that a customer left the bank, once she cancelled all current accounts.

We start our investigation by examining the impact of customer's demand for financial services as well as her skills regarding the usage of digital (financial) services, instrumented by *channel usage*, *business intensity* and *payment behavior*. The effect of *channel usage* likewise changes over time. As in 2015 only online-banking transactions had a spillover on mobile-banking adoption, in 2018 all channel transactions are associated positively with mobile-banking adoption. As we expected a high influence of ATM beside of online-banking transactions (Albesa, 2007; Curran and Meuter, 2005; Devlin and Yeung, 2003), we have to state that this effect is mostly not or only slightly significant. However, transactions by branch and call center generate much lower p-values. As a consequence not merely the usage of self-service channels, but rather the overall demand for financial services, amongst others instrumented by transaction counts in banking channels, in combination with online-banking skills are associated positively with mobile-banking adoption (supporting H1A and H2B, rejecting H2A).

We continue with the investigation of customer's *business intensity*, which uncovers mixed results. The coefficient of product usage[8] shows that the utilization of every additional product category, which also leads to a higher need to manage them efficiently, increases the probability of mobile-banking adoption by 6.7% to 15.5%, depending on the year of observation (supporting H1B). This finding is also congruent with online-banking literature (Gensler et al., 2012; Berger and Gensler, 2007; Hitt and Frei, 2002). However, actual customer profitability seems to be unrelated to mobile-banking adoption (rejecting H1C).

The relation between customer's *payment behavior* and mobile-banking adoption shows highly dynamic outcomes. Cash deposits and debitcard payments are the only variables that correlate significantly in every year of observation. We show that offline money transfers and cash withdrawals are associated negatively with mobile-banking adoption. Online money transfers, cash deposits, debitcard and credit card payments instead show a positive relation to mobile-banking adoption. People, who show digital skill in their payment behavior, seem to be more likely to adopt mobile-banking. (supporting H2C and H2E)

Finally, we focus on *customer demographics*. We find that in every year of our investigation age is associated negatively, which reveals that younger people adopt mobile-banking faster (supporting H3A). A negative influence of age on mobile-banking adoption is in line with prior literature (Carlin et al., 2019a; Cope et al., 2013; Laukkanen and Pasanen, 2008; Mattila, 2003), in marked contrast to our gender insight: Whereas literature finds that male customers have a higher adoption probability than females (Carlin et al., 2019a; Laukkanen and Cruz, 2012; Koenig-Lewis et al., 2010; Laukkanen and Pasanen, 2008; Mattila, 2003), we show that this effect vanishes gradually. While in 2015 the adoption probability of males was 25.7% higher than of females, the coefficient gets smaller over time and is no more significant in 2018. Most recently, men and women adopt mobile-banking equally (rejecting H3B).

8 Product usage measures, how many of the following distinct product categories are used: current, loan, deposit or custody account, credit card, share in the company/bank, savings at a building society, insurance.

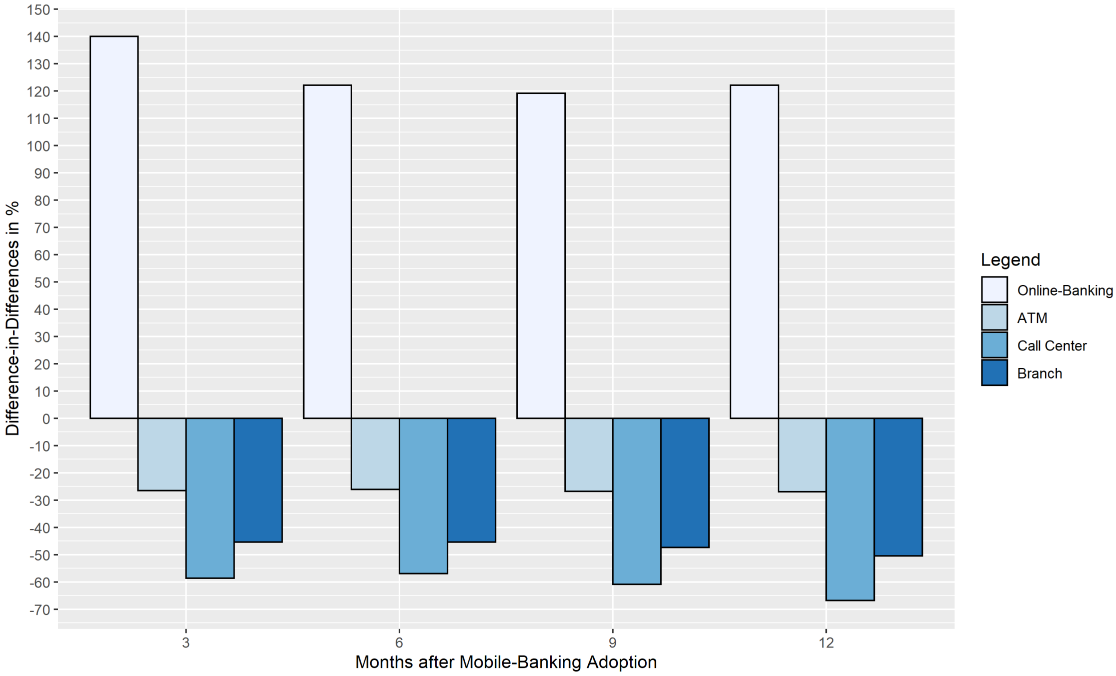

Figure B-1: Visualization of percentage changes in channel usage 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. The values correspond to the percentage changes documented in Table B-4.

Except for our profitability and gender insights, which uncover that most recently men and women adopt mobile-banking equally as well as that customer profitability is not associated to mobile-banking adoption, all results are in line with our expectations out of section 3.3.1. Clients with higher demand for financial services or higher skills regarding the usage of digital (financial) services adopt mobile-banking faster. Additionally, younger people are more likely to adopt mobile-banking.

3.6.2 Postadoption Analysis

3.6.2.1 Channel Usage

In the following, we provide detailed results of our DiD postadoption analysis. All tables present 3-month, 6-month, 9-month and 12-month (3m, 6m, 9m, 12m) DiD, which document β_3 out of equation 3, as well as the percentage change in comparison to the mean of the dependent variable of adopters one month before adoption. Furthermore, we distinguish between active and passive users by performing a median split of the sample on the count of mobile-banking transactions, which are performed on average per month after adoption.[9] The figures, which we provide in the following, visualize the 3-month, 6-month, 9-month and 12-month percentage changes in the full sample.

Figure B-1 visualizes the percentage changes in channel usage after mobile-banking adoption, Table B-

9 We calculate the average of monthly mobile-banking transactions after adoption by summing up all mobile-banking transactions of the client during our observation period relative to the count of months observed after customer's adoption.

	3m DiD		6m DiD		9m DiD		12m DiD	
	Coefficient	in %	Coefficient	in %	Coefficient	in %	Coefficient	in %
Full Sample								
Online-Banking	24.2900***	140.1%	21.1900***	122.2%	20.6600***	119.1%	21.1800***	122.1%
ATM	−2.0490***	−26.5%	−2.0170***	−26.0%	−2.0780***	−26.8%	−2.0800***	−26.9%
Call Center	−0.1127***	−58.7%	−0.1093***	−56.9%	−0.1169***	−60.9%	−0.1284***	−66.8%
Branch	−0.3680***	−45.3%	−0.3681***	−45.3%	−0.3844***	−47.4%	−0.4092***	−50.4%
Active User								
Online-Banking	38.9000***	239.4%	35.4600***	218.2%	35.5000***	218.5%	36.1500***	222.5%
ATM	−3.0760***	−33.7%	−3.2980***	−36.1%	−3.2930***	−36.1%	−3.3040***	−36.2%
Call Center	−0.1851***	−69.1%	−0.1720***	−64.2%	−0.1795***	−67.0%	−0.1761***	−65.7%
Branch	−0.4527***	−51.1%	−0.4533***	−51.1%	−0.4790***	−54.0%	−0.5189***	−58.5%
Passive User								
Online-Banking	9.6040***	52.1%	6.8250***	37.0%	5.4690***	29.7%	5.4530***	29.6%
ATM	−1.0220***	−16.1%	−0.7343***	−11.5%	−0.8589***	−13.5%	−0.8470***	−13.3%
Call Center	−0.0402	−34.6%	−0.0467	−40.2%	−0.0543*	−46.8%	−0.0814**	−70.1%
Branch	−0.2831***	−38.4%	−0.2828***	−38.4%	−0.2893***	−39.3%	−0.2974***	−40.4%

Table B-4: Changes in customer's channel usage 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. Table shows DiD coefficients, which correspond to β_3 out of equation 3, and the percentage change in comparison to the mean of the dependent variable of adopters one month before adoption. The treatment group of the DiD regression comprises 7,810 clients, who adopt mobile-banking during our observation period from January 2015 to December 2018 and are observable at least one month before adoption. The control group comprises matched controls of not-yet-treated clients. We report full sample results and further distinguish between active and passive users by performing a median split on the count of mobile-banking transactions, which are performed on average per month after adoption.

4 provides detailed results of these values. We find that mobile-banking adoption has a very strong augmentation effect on online-banking. Compared to the matched controls, monthly counts of online-banking transactions more than double on average after mobile-banking adoption and remain constant over time (DiD between 21.18 and 24.29, which correspond to a percentage change between +122.1% and +140.1%, respectively). For active user the effects are even stronger and result in an tripling of transaction counts relative to the matched controls. (DiD between 35.46 and 38.90, which correspond to a percentage change between +218.2% and +239.4%, respectively).

While online-banking transactions are augmented by mobile-banking, the usage of ATMs, call center and branches get substituted. Compared to the matched controls, monthly ATM transactions decline directly by roughly one quarter and stay constant over time (DiD between −2.02 and −2.08, which correspond to a percentage change between −26.0% and −26.9%, respectively). Monthly call center and branch transaction counts approximately halve after mobile-banking adoption (3m DiD = −0.11 and 3m DiD = −0.37, which correspond to a precentage change of −58.7% and −45.3%, respectively) with a little further decline over time (12m DiD = −0.13 and 12m DiD = −0.41, which correspond to a precentage change of −66.8% and −50.4%, respectively), compared to the matched controls. Once more, all documented effects are more pronounced for active mobile-banking users. Ultimately, mobile-banking has a large impact on customer's channel usage. These effects establish during the first quarter after mobile-banking adoption and persist in the long-term. As online-banking adoption from 1999 to 2007 augmented transactions in all other channels (Xue et al., 2011; Campbell and Frei, 2010), mobile-banking

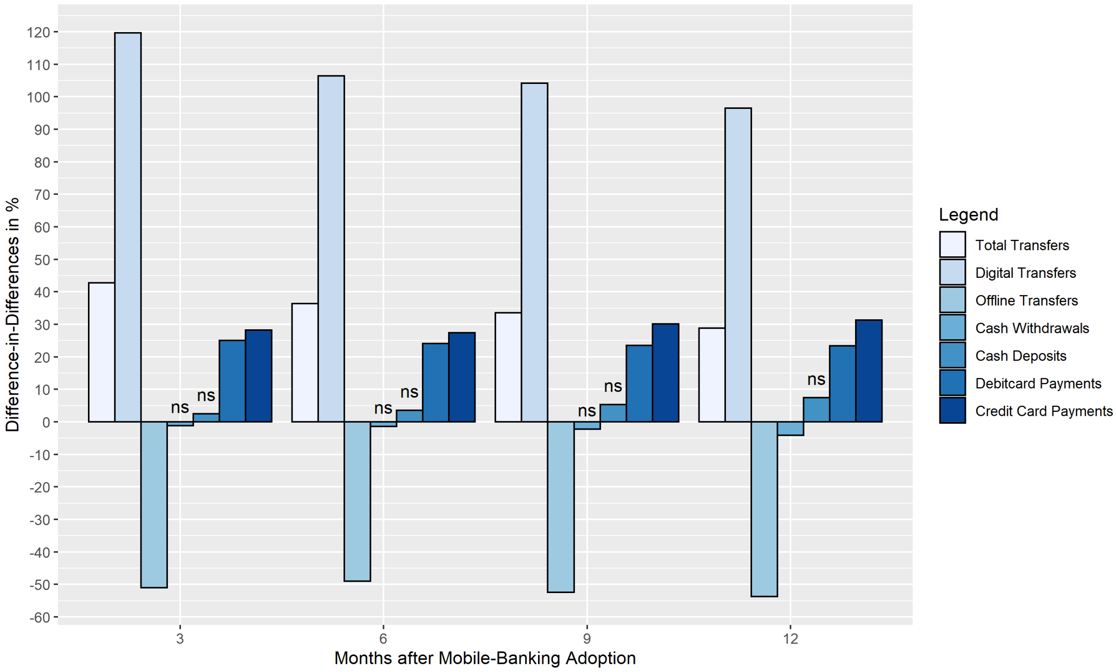

Figure B-2: Visualization of percentage changes in payment behavior 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. The values correspond to the percentage changes documented in Table B-5. Non-significant results are marked with *ns*.

adoption in 2015 to 2018 still augments online-banking transactions but heavily substitutes transactions in all non-digital channels (supporting H4).

3.6.2.2 Payment Behavior

Similar to section 3.6.2.1, Figure B-2 visualizes the percentage changes in payment behavior after mobile-banking adoption and Table B-5 provides detailed results of these values. Likewise, payment behavior changes intensely after mobile-banking adoption.

Total money transfers per month increase by +42.8% (3m DiD = 0.74) in the near-term and are even +28.8% (12m DiD = 0.50) higher compared to the matched controls one year after mobile-banking adoption. By dividing total money transfers into digital and offline transfers, we unveil even stronger differences between both groups. Mobile-banking adopters roughly double their digital transfers compared to the matched controls.[10] Again, this behavior starts directly after mobile-banking adoption (3m DiD = 1.13 or +119.7%) and is still observable one year later (12m DiD = 0.91 or +96.6%, supporting H5A). In order to identify the driver of this effect, we subdivide digital transfers into both groups of online- and mobile-banking transfers. The differences in digital transfers are driven by mobile- compared to online-banking transfers immediately after mobile-banking adoption (3m DiD of online-banking transfers = 0.52 < 3m DiD of mobile-banking transfers = 0.61). However, the share of mobile-banking transfers further increases over time (12m DiD of online-banking transfers = 0.35 << 12m DiD of mobile-banking

10 Digital transfers correspond to the sum of online- and mobile-banking transfers.

	3m DiD		6m DiD		9m DiD		12m DiD	
	Coefficient	in %	Coefficient	in %	Coefficient	in %	Coefficient	in %
Full Sample								
Total Transfers	0.7371***	42.8%	0.6263***	36.3%	0.5787***	33.6%	0.4969***	28.8%
Digital Transfers	1.1330***	119.7%	1.0070***	106.4%	0.9858***	104.1%	0.9141***	96.6%
Online-Banking Transfers	0.5237***	55.3%	0.4157***	43.9%	0.4066***	43.0%	0.3452***	36.5%
Mobile-Banking Transfers	0.6091***	–	0.5911***	–	0.5792***	–	0.5689***	–
Offline Transfers	−0.3957***	−51.0%	−0.3805***	−49.0%	−0.4070***	−52.5%	−0.4172***	−53.8%
Cash Withdrawals	−0.0395	−1.2%	−0.0469	−1.4%	−0.0745	−2.2%	−0.1378**	−4.1%
Cash Deposits	0.0075	2.5%	0.0107	3.5%	0.0163	5.4%	0.0228	7.5%
Debitcard Payments	1.3380***	25.1%	1.2860***	24.1%	1.2540***	23.5%	1.2470***	23.4%
Credit Card Payments	0.0242***	28.2%	0.0235***	27.5%	0.0258***	30.1%	0.0268***	31.3%
Active User								
Total Transfers	1.0880***	65.2%	0.9369***	56.1%	0.8595***	51.5%	0.8244***	49.4%
Digital Transfers	1.6140***	203.9%	1.4440***	182.5%	1.3990***	176.8%	1.3650***	172.5%
Online-Banking Transfers	0.5885***	74.4%	0.4349***	55.0%	0.4040***	51.0%	0.3880***	49.0%
Mobile-Banking Transfers	1.0260***	–	1.0090***	–	0.9948***	–	0.9772***	–
Offline Transfers	−0.5264***	−60.0%	−0.5072***	−57.8%	−0.5394***	−61.5%	−0.5408***	−61.7%
Cash Withdrawals	−0.0605	−1.6%	−0.1872**	−5.0%	−0.1942*	−5.2%	−0.2752***	−7.3%
Cash Deposits	0.0381*	10.1%	0.0288	7.6%	0.0443*	11.7%	0.0390	10.3%
Debitcard Payments	1.6350***	30.9%	1.5470***	29.2%	1.5900***	30.0%	1.5850***	29.9%
Credit Card Payments	0.0245***	33.8%	0.0312***	43.1%	0.0267***	36.8%	0.0379***	52.3%
Passive User								
Total Transfers	0.3846***	21.6%	0.3137***	17.7%	0.2915***	16.4%	0.1522*	8.6%
Digital Transfers	0.6493***	58.9%	0.5674***	51.5%	0.5653***	51.3%	0.4443***	40.3%
Online-Banking Transfers	0.4591***	41.7%	0.3975***	36.1%	0.4115***	37.3%	0.3048***	27.7%
Mobile-Banking Transfers	0.1902***	–	0.1699***	–	0.1539***	–	0.1395***	–
Offline Transfers	−0.2647***	−39.2%	−0.2536***	−37.6%	−0.2739***	−40.6%	−0.2921***	−43.3%
Cash Withdrawals	−0.0197	−0.7%	0.0923	3.1%	0.0413	1.4%	−0.0089	−0.3%
Cash Deposits	−0.0234	−10.2%	−0.0078	−3.4%	−0.0132	−5.7%	0.0035	1.5%
Debitcard Payments	1.0400***	19.3%	1.0230***	19.0%	0.9104***	16.9%	0.8941***	16.6%
Credit Card Payments	0.0240***	24.2%	0.0158**	16.0%	0.0251***	25.3%	0.0157*	15.9%

Table B-5: Changes in customer's payment behavior 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. Table shows DiD coefficients, which correspond to β_3 out of equation 3, and the percentage change in comparison to the mean of the dependent variable of adopters one month before adoption. The treatment group of the DiD regression comprises 7,810 clients, who adopt mobile-banking during our observation period from January 2015 to December 2018 and are observable at least one month before adoption. The control group comprises matched controls of not-yet-treated clients. We report full sample results and further distinguish between active and passive users by performing a median split on the count of mobile-banking transactions, which are performed on average per month after adoption.

transfers = 0.57). Hence, in the long-term mobile-banking adopters still perform more online-banking transfers compared to the matched controls, but likewise seem to get used to the functionalities of mobile-banking over time and subsequently shift portions of digital transfers from online- to mobile-banking.

On the other side, monthly offline transfers are substituted after mobile-banking adoption. The number of these offline transfers halves directly after mobile-banking adoption (3m DiD = −0.40 or −51%) and, again, stays constant over time (12m DiD = −0.42 or −53.8%, supporting H5B). Similar to our results regarding the overall transactions in non-digital channels (see section 3.6.2.1), the substitution in offline money transfers starts during the first quarter after mobile-banking adoption and persists in the long-term afterwards. Once more, all coefficients are even stronger for active compared to passive mobile-banking users.

Cash withdrawals and deposits stay unchanged in the mid-term, as we do not observe significant 3m, 6m or 9m differences between mobile-banking adopters and their matched controls. In the long-term instead, we document a −4.1% reduction in cash withdrawals (12m DiD = −0.14, which leads to partial support for H5C). This long-term decrease in cash withdrawals is accompanied by a surge in the usage of cashless payment methods, namely debitcard and credit card payments. Their usage rises immediately after mobile-banking adoption by +25.1% (3m DiD = 1.34) and +28.2% (3m DiD = 0.02) and stabilizes in the long-term at +23.4% (12m DiD = 1.25) and +31.3% (12m DiD = 0.03), respectively, compared to their matched controls (supporting H5D). Once more, all effects are even stronger for active mobile-banking users.

As hypothesized in section 3.3.2, mobile-banking adoption is associated with remarkable changes in customer's payment behavior. This change decomposes into an increase in digital money transfers in conjunction with stronger utilization of cashless payment methods. Offline money transfers as well as cash usage instead decrease after adoption. Except for cash-withdrawals, where the behavior of the client shifts rather in the long-term, all other changes establish during the first quarter after mobile-banking adoption and show stable differences compared to the matched controls over time.

3.6.2.3 Business Intensity and Customer Churn

Figure B-3 visualizes the percentage changes in product usage, customer profitability and 12-month churn rate after mobile-banking adoption. Table B-5 provides detailed results of these values. We find an increase in product usage compared to the matched controls.[11] As hypothesized in section 3.3.1 and ascertained in section 3.6.1, individuals with higher demand for financial services, among others measured by product usage, are more likely to adopt mobile-banking. This difference in product usage increases additionally by +4.1% (3m DiD = 0.12) in the short term and subsequently ascends to +4.8%

11 Product usage measures, how many of the following distinct product categories are used: current, loan, deposit or custody account, credit card, share in the company/bank, savings at a building society, insurance.

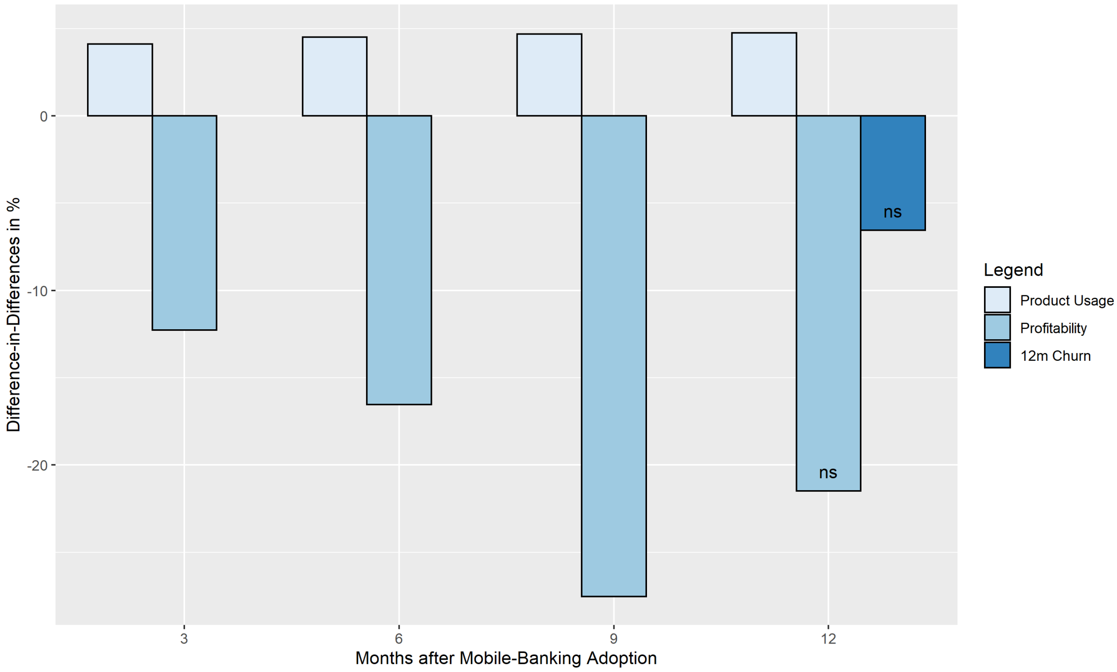

Figure B-3: Visualization of percentage changes in product usage, profitability and 12m churn rate 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. The values correspond to the percentage changes documented in Table B-6. Non-significant results are marked with *ns*.

(12m DiD = 0.14, supporting H6A) one year after mobile-banking adoption. Mobile-banking adopters seem to acquire new product types and by this enlarge their relationship to the bank.

With respect to customer profitability we find mixed results. Profitability declines short-dated by −12.3% (3m DiD = −1.87) and further decreases to −27.5% (9m DiD = −4.20) nine months after mobile-banking adoption in comparison to the matched controls. In the long term instead, this effect vanishes and we do not find a significant difference in customer profitability between mobile-banking adopters and non-adopters (supporting H6B partially). These results are in line with Campbell and Frei (2010) as well as Xue et al. (2011), who show a decline in customer profitability during the first months after online-banking adoption, but no persistence in the long-term. A reason for this phenomenon could be that the increase in product usage, which should lead to higher profits, could be overcompensated short dated by more efficient money management capabilities (Campbell and Frei, 2010). Beside others, the decline in offline money transfers shown in section 3.6.2.2, which are normally associated with higher fees compared to digital transfers, could lead to a reduction in short-term profits. Furthermore, a less frequent utilization of unsecured debt (e.g. overdraft) after mobile-banking adoption, which is reported by Becker et al. (2021), would also reduce profits by lowering rates of interest paid by the customer.

Our final aspect of postadoption analysis investigates the association of mobile-banking adoption with customer's 12-month churn rate. Table B-11, which we provide in Appendix 3.9.5, complements Table B-6 by providing the complete DiD-regression of mobile-banking adoption on 12-month customer churn

	3m DiD		6m DiD		9m DiD		12m DiD	
	Coefficient	in %	Coefficient	in %	Coefficient	in %	Coefficient	in %
Full Sample								
Product Usage	0.1203***	4.1%	0.1317***	4.5%	0.1368***	4.7%	0.1390***	4.8%
Profitability	−1.8720*	−12.3%	−2.5210*	−16.5%	−4.2000**	−27.5%	−3.2750	−21.5%
12m Churn							−0.0014	−6.6%
Active User								
Product Usage	0.1347***	4.8%	0.1552***	5.5%	0.1529***	5.4%	0.1675***	5.9%
Profitability	−1.4160	−10.9%	−3.1710	−24.4%	−6.7650**	−52.0%	−4.3250	−33.2%
12m Churn							−0.0076**	−34.4%
Passive User								
Product Usage	0.1062***	3.5%	0.1084***	3.6%	0.1208***	4.0%	0.1105***	3.7%
Profitability	−2.3190*	−13.3%	−1.8540	−10.6%	−1.5570	−8.9%	−2.1390	−12.2%
12m Churn							0.0052	26.7%

Table B-6: Changes in customer's product usage, profitability and 12m churn rate. DiD in product usage and profitability are examined 3-month, 6-month, 9-month and 12-month after mobile-banking adoption. 12m churn rate is measured by a 12-month DiD regression having an indicator variable on the left hand side that equals to 1, if the customer left the bank, and zero otherwise (we declare that a customer left the bank, once she cancelled all current accounts). Table shows DiD coefficients, which correspond to β_3 out of equation 3, and the percentage change in comparison to (1) the sample mean of adopters one month before adoption for product usage and profitability as well as (2) the sample mean of the matched controls twelve months after adoption for 12m churn rate. The treatment group of the DiD regressions for product usage and profitability comprise 7,810 clients, who adopt mobile-banking during our observation period from January 2015 to December 2018 and are observable at least one month before adoption. The treatment group of the DiD regression for 12m churn rate is further restricted to those 7,312 clients, who adopt before January 2018 and are therefore observable at least 12 months after their adoption. The control groups comprise matched controls of not-yet-treated clients. We report full sample results and further distinguish between active and passive users by performing a median split on the count of mobile-banking transactions, which are performed on average per month after adoption.

rate and documents that a non-adopter leaves the bank within the next 12 months after matching with a probability of 2.2%.[12] This churn rate is significantly associated with active mobile-banking usage, as it decreases by −34.4% after mobile-banking adoption (12m DiD of active mobile-banking user = −0.0076). Passive usage instead is not associated with a statistically significant reduction in 12-month customer churn rate (supporting H6C partially).

3.7 Discussion and Conclusion

In this paper, we investigate drivers of mobile-banking adoption and resulting changes in client's banking behavior. An empirical investigation of drivers of mobile-banking adoption as well as postadoption consequences has been under-researched in prior literature. We perform multivariate analysis of large-scale individual-level panel data to fill this gap.

During our observation period from 2015 to 2018 client's demand for financial services as well as her skills

12 We can derive the average churn-rate of a non adopter by calculating $\alpha_t + \beta_2$ of equation 3. As all mobile-banking adopters as well as all matched non-adopters did not leave the bank until matching, α_t equals to zero during all observed months. Hence, we derive the average churn rate of a matched non-adopter by observing β_2, which conforms to 0.0220 or 2.2%.

Hypothesis		Result
Reasons of Mobile-Banking Adoption		
H1A:	Higher transaction count in banking channels is associated with faster mobile-banking adoption.	S
H1B:	Higher product usage is associated with faster mobile-banking adoption.	S
H1C:	Higher customer profitability is associated with faster mobile-banking adoption.	R
H2A:	The usage of ATMs is associated positively with mobile-banking adoption.	R
H2B:	The usage of online-banking is associated positively with mobile-banking adoption.	S
H2C:	Higher count in online money transfers is associated with faster mobile-banking adoption.	S
H2D:	Stronger usage of cashless payment methods, namely debitcards and creditcards, is associated positively with mobile-banking adoption.	S
H3A:	Customer's age is associated negatively with mobile-banking adoption.	S
H3B:	Male customer's are more likely to adopt mobile-banking than females.	R
Changes after Mobile-Banking Adoption		
H4:	Mobile-banking adoption is associated with altered transaction counts in other channels.	S
H5A:	Mobile-banking adoption is associated with an increase in digital money transfers.	S
H5B:	Mobile-banking adoption is associated with a decrease in offline money transfers.	S
H5C:	Mobile-banking adoption is associated with a decrease in the utilization of cash.	PS
H5D:	Mobile-banking adoption is associated with an increase in the utilization of cashless payment methods.	S
H6A:	Mobile-banking adoption is associated with an increase in product usage.	S
H6B:	Mobile-banking adoption is associated with a short-term decrease in customer profitability.	PS
H6C:	Mobile-banking adoption is associated with a decrease in customer churn rate.	PS

Table B-7: Summary of hypotheses tests. Result is abbreviated by S, supported; PS, partially supported; R, rejected.

regarding the usage of digital (financial) services, instrumented by channel usage, business intensity and payment behavior, strongly correlate with mobile-banking adoption. Furthermore, we find that younger people are more likely to adopt mobile-banking. In contrast to survey-based literature, we document that, most recently, men and women adopt mobile-banking equally.

On the basis of our adoption insights, we perform risk set matching in order to control for potential self-selection effects. We investigate changes in banking behavior after mobile-banking adoption by using difference-in-differences techniques and derive post-adoption changes relative to our matched controls. With respect to customer's channel usage, we examine strong augmentation as well as substitution effects. As monthly counts of online-banking transactions increase by roughly +130% after mobile-banking adoption, the usage of non-digital channels is heavily substituted and transaction counts of ATMs, call center and branches decrease by roughly −25% to −65%. Hence, mobile-banking adoption crucially impacts omni-channel transactions of the customer. In contrast to online-banking adoption from 1999 to 2007, where transactions in all other channels where augmented (Xue et al., 2011; Campbell and Frei, 2010), mobile-banking adoption in 2015 to 2018 still augments online-banking transactions but substitutes transactions in all non-digital channels remarkably.

In addition, customer's payment behavior is influenced by mobile-banking. Total transfers increase heavily, which is driven by online- and mobile-banking transfers, while the number of offline transfers drop by roughly -50%. The usage of cash is reduced and gets substituted by cashless payment methods, namely debitcards and credit cards. The observed post-adoption effects establish during the first quarter after mobile-banking adoption, stay persistent over time and are even stronger for active in comparison to passive mobile-banking users.

Furthermore, we examine the association of mobile-banking adoption with product usage, customer's profitability and 12-month churn rate. We observe an increase in product usage, which establishes immediately after adoption and climbs up $+5\%$ in the long-term. As customer's profitability declines short-dated by up to -28% compared to the matched controls, this effect vanishes in the long-term and we do not find significant differences in profitability between mobile-banking adopters and non-adopters 12-months after adoption. Ultimately, we analyze the association of mobile-banking with 12-month churn rate. Although active mobile-banking usage is not associated with an increase in customer's profitability, it is potentially accompanied with an increase in customer lifetime value (CLV), as customer's 12-month churn rate declines by -34%.

These results contribute to the literature in several ways and are largely consistent with our theoretic assumptions. A higher need for financial services and broader skills in utilizing digital channels as well as payment methods are associated with faster mobile-banking adoption. These insights are in line with the models of Rogers (1983), Davis and Davis (1989) and Venkatesh et al. (2003) and similar to the findings of Lee and Lee (2001) and Xue et al. (2011). Furthermore, we correspond to Xue et al. (2011) and Campbell and Frei (2010), who investigate changes after online-banking adoption, as we document an increase in overall transactions with the bank, augmentation and substitution effects in other banking channels, higher product usage and lower churn rates after mobile-banking adoption. In addition, we find evidence for our hypotheses that the previously discovered increase in financial transparency through mobile-banking (Becker et al., 2021; Levi and Benartzi, 2020; Carlin et al., 2019a) enhances card payments and substitutes cash usage, which was formerly used particularly to obtain an overview about current budgets (Bartzsch et al., 2019; Kalckreuth et al., 2014). This is also consistent with Levi and Benartzi (2020), who document a reduction in cash-withdrawals after mobile-banking adoption. Our methodology as well as our results are extendable to other omni-channel service industries, such as retailing, wholesale or other types of financial services. Our findings are, for example, accompanied by the outcomes of Soysal and Krishnamurthi (2016), who analyze sales in retail stores and find, among others, an increase in customer's overall spending with the retailer after adoption of the lower-quality, lower-price factory outlet channel.

Moreover, our findings are potentially useful in practice for several reasons. Our adoption analysis enables bank marketers to address their mobile-banking offer, geared to the target group. Furthermore, our post-adoption analysis supports bank managers as well. First, banks review their distribution strategy frequently. On the basis of our results managers are able to anticipate changes in omni-channel usage behavior to offer adequate and cost-effective omni-channel banking services. In contrast to online-banking adoption, which augmented transactions in other channels from 1999 to 2007 (Xue et al., 2011; Campbell and Frei, 2010), mobile-banking adoption in 2015 to 2018 heavily substitutes transactions in all non-digital channels. This insight gets further supported by our examination of customer's payment behavior, where we find a distinct drop in offline as well as a surge in digital money transfers, which are driven by online- and mobile-banking transfers. As mobile-banking usage as well as overall customer digitization increase, banks will have to further adjust channel related capital expenditures to extend digital functionalities while diminishing analogues services in order to maintain a cost effective business model.

Second, payment processing is a major service of banks. Our results show that mobile-banking is associated with augmentation of card payments, substitution of cash usage and an increase in the overall number of money transfers. Banks produce valuable data, which can be used to generate individualized offers for their customers (Massi et al., 2019). If not already initiated, they should establish data science capabilities to generate value-added services by using these additional data. Otherwise this chance of offering new and by customers esteemed services could remain unexploited. Beyond, retailers benefit from lower costs of cash management (Deutsche Bundesbank, 2019a). Government and regulators, who attempt to reduce cash usage for reasons of preventing tax evasion and crime (Massi et al., 2019; Deutsche Bundesbank, 2018; Judson, 2017) as soon as boost economic growth (Massi et al., 2019; Tee and Ong, 2016), should support mobile-banking usage in the society as well.

Third, bank managers need insights whether mobile-banking strengthens the relationship to their customers or reduces business intensity and accelerating customer churn (e.g. to a fully digital fintech), once they get used to the amenities of digital banking. On the basis of the observed outcomes banks should encourage customers to adopt as well as actively use mobile-banking.

Eventually, our paper faces several limitations and points out opportunities for further research. First, our data are limited to a single bank. In order to receive more general insights, a multi-bank data set should be incorporated. By this, results could overcome the dependence on the strategy and environmental impacts of a singular bank. Second, although we perform risk set matching with reasonable results it is still possible that the decision to adopt mobile-banking is determined by unobserved influences, which would undermine our causal interpretation. Third, our DiD approach investigates changes up to 12-months after mobile-banking adoption. Therefore, long-term effects beyond one year after adoption are not examined. An investigation of longer time-periods could generate deeper insights. Finally, we document a reduction in customer's 12-month churn rate, which leads potentially to an increase in customer lifetime value (CLV).

However, on the basis of our data we are not able to analyze, whether or not potential interactions with other accounts held by the customer at direct banks or fintechs are also influenced by mobile-banking adoption.[13] On the basis of our results one could hypothesize that these transactions stay at least stable or diminish after mobile-banking adoption. Such insights would complement our suggestion that banks should encourage customers to adopt and actively use mobile-banking.

13 By incorporating e.g. data about payment transactions, such an analysis would be possible.

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3.9 Appendices

3.9.1 Payments Statistics of Deutsche Bundesbank

	2010	2011	2012	2013	2014	2015	2016	2017	2018
Offline Money Transfers	940.2	896.5	847.2	816.1	623.5	612.2	570.5	521.3	482.9
	[/]	[−4.6%]	[−5.5%]	[−3.7%]	[−23.6%]	[−1.8%]	[−6.8%]	[−8.6%]	[−7.4%]
Online Money Transfers	4931.6	5176.0	5303.8	5401.3	5009.6	5407, 5	5615.7	5777.3	5985.2
	[/]	[5.0%]	[2.5%]	[1.8%]	[−7.3%]	[7.9%]	[3.9%]	[2.9%]	[3.6%]
Cash Withdrawals	2326.4	2377.4	2385.0	2352.8	2256.8	2359.6	2345.6	2271.7	2223.5
	[/]	[2.2%]	[0.3%]	[−1.4%]	[−4.1%]	[4.6%]	[−0.6%]	[−3.2%]	[−2.1%]
Cash Deposits	275.0	279.6	273.8	271.9	262.7	265.5	265.2	257.1	257.2
	[/]	[1.7%]	[−2.1%]	[−0.7%]	[−3.4%]	[1.1%]	[−0.1%]	[−0.6%]	[−0.6%]
Debitcard Payments	2196.3	2399.7	2579.1	2885.3	2595.1	2722.6	2963.4	3275.4	3913.8
	[/]	[9.3%]	[7.5%]	[11.9%]	[−10.1%]	[4.9%]	[8.8%]	[10.5%]	[19.5%]
Creditcard Payments	447.9	501.2	559.7	681.5	762.5	879.0	984.0	1100.8	1260.3
	[/]	[11.9%]	[11.7%]	[21.8%]	[11.9%]	[15.3%]	[11.9%]	[11.9%]	[14.5%]

Table B-8: Key figures explaining the nationwide payment behavior in Germany based on Deutsche Bundesbank (2020a,b,c). Column 1 shows the dimension of interest. Columns 2 to 10 document the number of transactions in millions in that particular year. Percentage changes relative to the preceding year are printed in parentheses.

3.9.2 Variable Definition

Variable	Definition
Demographics	
Age	Age of the customer (in years)
Male	Indicator variable, which equals one, if the customer is male, and zero otherwise
Channel Usage	
Mobile-Banking	Count of mobile-banking transactions (per month)
Online-Banking	Count of online-banking transactions (per month)
ATM	Count of ATM transactions (per month)
Call Center	Count of call center transactions (per month)
Branch	Count of branch transactions (per month)
Payment Behaviour	
Offline transfers	Count of money transfers, which are performed through non-digital channels (ATM, call center, branch) (per month)
Online transfers	Count of money transfers, which are performed through digital channels (online-banking, mobile-banking) (per month)
Cash withdrawals	Count of cash withdrawals (ATM, branch) (per month)
Cash deposits	Count of cash deposits (ATM, branch) (per month)
Debitcard payments	Count of debitcard payments (per month)
Credit Card payments	Count of credit card payments (per month)
Business Intensity	
Product usage	Count of distinct product categories (current, loan, deposit or custody account, credit card, share in the company/bank, building society savings, insurance), which are used by the customer (end of month)
Customer profitability	Monthly gross margin, measured by the banks internal control system (in euro)
Wealth Status	
Salary	Sum of all salary or pension payments (per month in euro)
Balance of Currents	Sum of balances of current accounts (end of month in euro)
Balance of Deposits	Sum of balances of deposit accounts (end of month in euro)
Balance of Investments	Sum of balances of investment accounts (end of month in euro)
Balance of Loans	Sum of balances of loan accounts (end of month in euro)

Table B-9: Definition of variables.

3.9.3 Types of Transactions per Channel

Transaction	Mean
Branch	
Sum of all Transactions	1.27
thereof Money Transfer	1.00
thereof Money Withdrawal	0.19
thereof Money Deposit	0.06
thereof Print of Account Statement	0.02
Call Center	
Sum of all Transactions	1.97
thereof Account Inquiry	0.71
thereof General Call	0.62
thereof Money Transfer	0.64
ATM	
Sum of all Transactions	6.43
thereof Money Withdrawal	2.71
thereof Print of Account Statement	2.20
thereof Account Inquiry	1.29
thereof Money Transfer	0.12
thereof Money Deposit	0.11
Online-Banking	
Sum of all Transactions	31.07
thereof Account Inquiry	24.25
thereof LogIn	4.35
thereof Money Transfer	1.87
thereof View Account Statement	0.57
thereof Other Service	0.03
Mobile-Banking	
Sum of all Transactions	5.53
thereof Account Inquiry	4.25
thereof LogIn	1.18
thereof Money Transfer	0.06
thereof View Account Statement	0.04
thereof Other Service	0.00

Table B-10: Distribution of transaction types across banking channels. Table shows the mean of the number of clients monthly transactions per channel. Similar to Table B-2, we provide descriptive statistics after customers first usage of the respective channel. Thus, we remove observations of those customers, who do not use the respective channel in order to reduce skewness of our descriptive results. As customers are able to inquire multiple accounts during one login-session, the online- and mobile-banking transaction counts for *account inquiry* are higher than those for *LogIn*.

3.9.4 Matching Results for the DiD Analysis

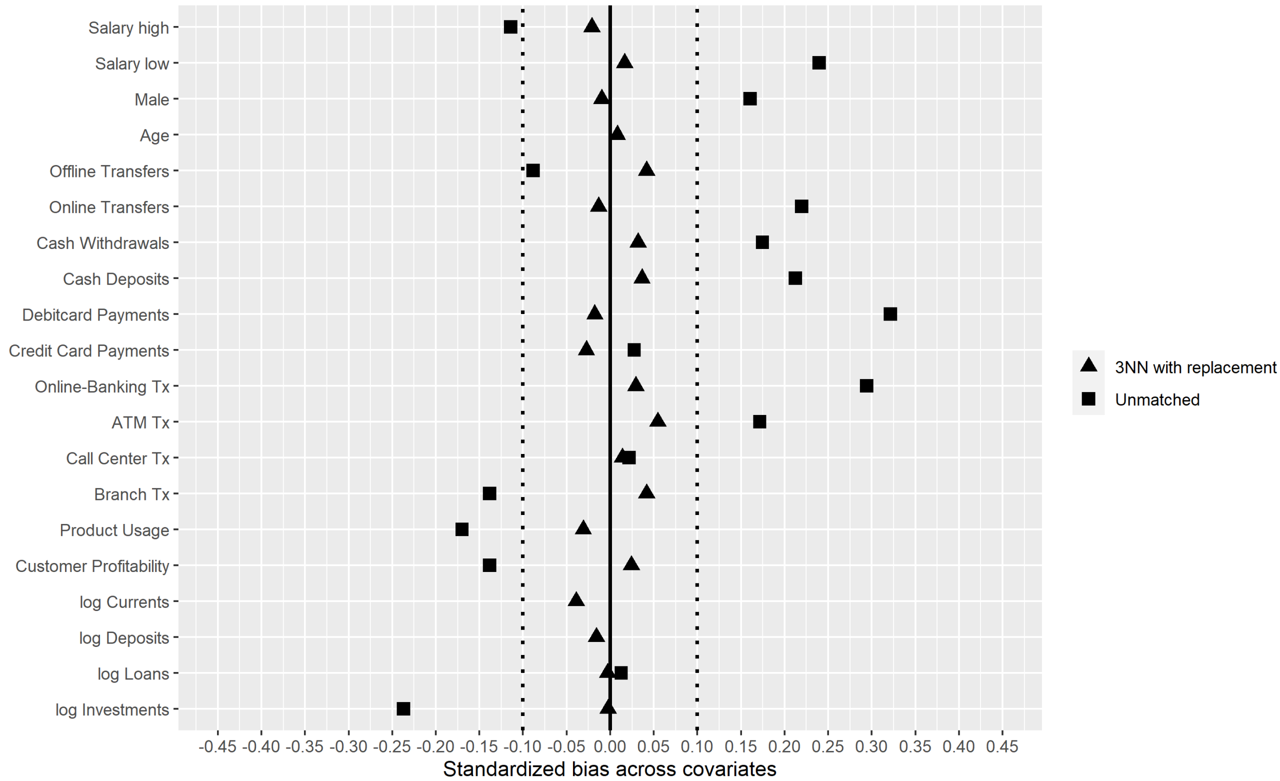

Figure B-4: Standardized bias across covariates before and after matching. We perform risk set matching, in which a treated client is matched to a not-yet-treated client, who exhibit similar time-dependent covariates up to the moment when the treatment occurs. We perform matching with replacement and match each treated unit with the three closest untreated neighbors. We enforce exact matching on month of adoption and an indicator variable, whether or not the customer already uses online banking. The Figure's x-axis shows the standardized bias (SB), y-axis prints the covariates of interest. The SB before matching (Unmatched) is visualized by squares, the SB after matching (3NN with replacement) is visualized by triangles. The performance measure of Harder et al. (2010), who recommend an SB of less than 0.1, is visualized by vertical dotted lines.

3.9.5 Detailed Results of Customer Churn DiD

	12-month customer churn rate
Treatment	-0.0000
	(0.0000)
Post	0.0220^{***}
	(0.0016)
Treatment:Post	-0.0076^{**}
	(0.0028)
Num. obs.	$32,813$
R^2 (full model)	0.0120
Adj. R^2 (full model)	0.0108

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

Table B-11: Detailed results of difference-in-differences regression for active mobile-banking users, having 12-month customer churn rate on the left hand side. The treatment group of the DiD regression comprises 3,907 clients, who adopt mobile-banking before January 2018, are observable at least one month before adoption and perform above median monthly mobile-banking transactions after their adoption. The control group comprises matched controls of not-yet-treated clients.

4 Empirische Evidenz zu Eigenschaften von Online- bzw. Mobile-Banking Kunden in Deutschland

Dieser Artikel wurde wie folgt veröffentlicht:

Becker, M. (2019). Empirische Evidenz zu Eigenschaften von Online- bzw. Mobile-Banking Kunden in Deutschland. Zeitschrift für Bankrecht und Bankwirtschaft, 31(1), 42-58.

Vorspann

Der Finanzdienstleistungssektor verändert sich durch Digitalisierung massiv. Online- bzw. Mobile-Banking stellen mittlerweile wesentliche Plattformen in dessen Multi-Kanal-Vertrieb dar. Für das zeitgemäße Management dieser digitalen Kanäle sind fundierte Kenntnisse über ihre Nutzerstrukturen essentiell. Hierzu identifiziert und diskutiert der vorliegende Beitrag theoretische Modelle und insbesondere 26 empirische Studien, die Aussagen zu Eigenschaften von Online- bzw. Mobile-Banking Kunden in Deutschland treffen. Diese werden studienübergreifend visualisiert und führen anschließend zu einer Charakterisierung der Kunden. Neben der Zusammenfassung der inhaltlichen Ergebnisse findet auch eine kritische Würdigung des methodischen Vorgehens der betrachteten Studien statt. Abschließend werden Lücken der bisherigen Literaturlandschaft dargelegt und relevante Fragestellungen für künftige Beiräge aufgezeigt.

4.1 Einleitung

Kreditinstitute im Allgemeinen und Retailbanken im Speziellen forcieren insbesondere die Digitalisierung ihres Leistungsangebotes. Der Wettbewerbsdruck, der sowohl durch bestehende Wettbewerber als auch durch neu auftretende FinTechs geprägt ist, nimmt aktuell rapide zu. In diesem Kontext wird insbesondere die Kundenschnittstelle der Banken massiv angegriffen.[1] Diese wird bisher durch diverse Vertriebs- und Kommunikationskanäle – insbesondere Filialen, SB-Automaten (Geldausgabeautomaten und Kontoauszugsdruckern), Call-Center, Sprachcomputer, Online- und Mobile-Banking – und somit durch einen Multi-Kanal-Vertrieb besetzt.[2] Abbildung C-1 kategorisiert diese anhand der Dimensionen Physisch/Digital bzw. Selbstbedient/Personalgestützt. Die Distributionskanäle Online- bzw. Mobile-Banking und deren Nutzer, die im Fokus des vorliegenden Beitrags stehen, gehören zu den digital-selbstbedienten Kanälen und sind visuell hervorgehoben.

Multi-Kanal-Vertrieb wird im gesamten Finanzdienstleistungssektor seit Jahren praktiziert und findet sich dort in besonders ausgeprägter Form.[3] Das Management von diesem wird nach Wirtz (2002, S. 1) folgendermaßen definiert: „[Multi-Kanal-Management] lässt sich als die integrierte und koordinierte Entwicklung, Gestaltung und Steuerung von Produkt- und Informationsflüssen über multiple Vertriebskanäle zur Optimierung des Distributionsmanagements verstehen.“

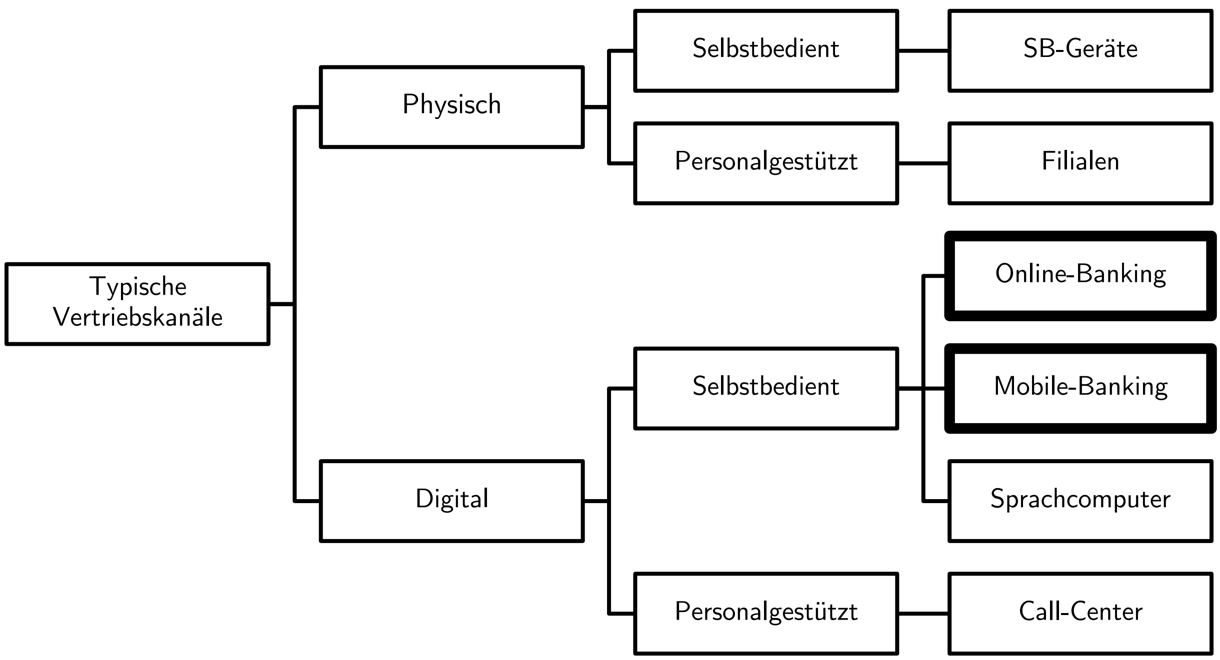

Abbildung C-1: Kategorisierung der üblichen Vertriebskanäle im Finanzdienstleistungssektor[4]

[1] Vgl. McWaters (2017, S. 86 ff.), Brandl & Hornuf (2017, S. 2), Dorfleitner & Hornuf (2016, S. 14 f.).

[2] Vgl. Wendel (2004), Liu, Abhishek & Li (2017, S. 2 f.), Dupas, et al. (2017, S. 12).

[3] Vgl. Black et al. (2002, S. 161).

[4] Eigene Darstellung. In Anlehnung an Liu, Abhishek und Li (2017) S. 3.

Die Entwicklung neuer Absatzmöglichkeiten, Verbesserung des Kundenerlebnisses sowie die Senkung der Betreuungskosten stehen regelmäßig im Vordergrund und sind wesentliche Aufgaben.[5] In den letzten Jahrzehnten haben Banken große Investitionen in den Auf- und Ausbau ihres Multi-Kanal-Vertriebes getätigt. Beginnend in den 1970er Jahren mit der Installation von SB-Automaten über die Etablierung von Call-Center in den 1990ern bis hin zur Fokussierung von Online- bzw. Mobile-Banking in den späten 1990ern und insbesondere den ersten Jahren des 21. Jahrhunderts.[6]

Während die Anpassung des Multi-Kanal-Vertriebes bisher in langsamen Schritten über Jahrzehnte hinweg erfolgte, ist durch die Digitalisierung mit kurzfristigen und besonders tiefgreifenden Veränderungen zu rechnen. Bundesweite Veränderungen lassen sich u.a. durch Publikationen der Deutsche Bundesbank sowie des Statistischen Bundesamtes ermitteln. Tabelle C-1 zeigt auf Basis dieser Studien ausgewählte Eigenschaften des deutschen Finanzwesens und vergleicht die Jahre 2013 und 2017.[7] *Abschnitt (A)* verdeutlicht, bei flüchtiger Beurteilung, nur moderate Veränderungen im Multi-Kanal-Vertrieb von Banken. Ein Ausbau des SB-Automaten Netzes um 2,6%, eine erhöhte Ausstattung privater Haushalte mit PCs und Mobiltelefonen um 5,6% bzw. 3,0% sowie eine daraus resultierende Steigerung der Nutzerbasis von Online-Banking um 9,6% lassen zunächst nur marginale Veränderungen erahnen. Konträr zu dieser Ersteinschätzung zeigt sich hingegen die Situation im Filialnetz deutscher Finanzdienstleister: Dieses wurde im gleichen Zeitraum um 20,6% reduziert. Zu einer detaillierten Betrachtung eignet sich die Auseinandersetzung mit dem Zahlungsverkehr in Deutschland. Dieser wird einerseits über standardisierte Schnittstellen abgewickelt und kann dadurch landesweit dokumentiert werden. Andererseits repräsentiert er die regelmäßigste Interaktion zwischen Kunde und Bank, kann über alle Kanäle aus Abbildung C-1 abgewickelt werden und informiert somit kurzfristig über Veränderungen. *Abschnitt (B)* visualisiert ausgewählte Kennzahlen und präsentiert tiefgreifende Veränderungen: Rückgänge zwischen 33,6% und 37,0% in bedienten sowie Zuwächse von bis zu 54,5% in selbstbedienten Transaktionsarten zeigen die radikalen und kurzfristigen Veränderungen, die von 2013 bis 2017 und damit in lediglich 4 Jahren stattgefunden haben. Der vorliegende Beitrag setzt inmitten dieser Veränderung an und hilft dem Management von Finanzdienstleistern Konsequenzen für das Multi-Kanal-Management abzuleiten. Im Fokus stehen die digitalen Distributionskanäle Online- und Mobile-Banking, die als Treiber für die gezeigten Veränderungen identifiziert werden können. Zur optimalen Ausgestaltung dieser Kanäle besteht für das Multi-Kanal-Management ein wesentlicher Informationsbedarf darin, die Eigenschaften und Charakteristika der jeweiligen Nutzergruppe zu kennen. Zur Bedienung dieses Informationsbedarfes wird im Folgenden Literatur, die über empirische Befunde einen Beitrag zur Beantwortung dieser Fragestellung leistet, visualisiert und diskutiert. Anschließend können Bankverantwortliche auf dieser

[5] Vgl. Wendel (2004), Barrué, Staib und Stegmeier (2010, S. 9), Baxter und Vater (2014, S. 4).

[6] Vgl. Barrué, Staib und Stegmeier (2010, S. 8), Liu, Abhishek und Li (2017, S. 1).

[7] Vgl. Deutsche Bundesbank (2018), Statistisches Bundesamt (2018), Statistisches Bundesamt (2014).

	Anzahl/Anteil 2013	Anzahl/Anteil 2017	Veränderung 2013 - 2017
Abschnitt (A): Veränderung in Vertriebskanälen			
Anzahl SB-Automaten	82.761	84.939	+ 2,6%
Anteil Haushalte mit PC	85,2%	90,0%	+ 5,6%
Anteil Haushalte mit Mobiltelefon	92,7%	95,5%	+ 3,0%
Anteil Online-Banking-Nutzer	52%	57%	+ 9,6%
Anzahl Filialen	38.021	30.172	- 20,6%
Abschnitt (B): Zahlungsverkehr			
Anzahl beleghafte Überweisungen	816 Mio.	520 Mio.	- 36,3%
Anzahl beleglose Überweisungen	5.401 Mio.	5.768 Mio.	+ 6,8%
Anzahl Bargeldeinzahlungen Filiale	177,2 Mio.	111,7 Mio.	- 37,0%
Anzahl Bargeldauszahlungen Filiale	237,8 Mio.	157,9 Mio.	- 33,6%
Anzahl Bargeldeinzahlungen Geldautomat	94,7 Mio.	146,3 Mio.	+ 54,5%
Anzahl Bargeldauszahlungen Geldautomat	2.115 Mio.	2.107 Mio.	- 0,4%
Anzahl Kartenzahlungen	3.633 Mio.	4.494 Mio.	+ 23,7%

Tabelle C-1: Veränderungen des Finanzwesens in Deutschland in den Jahren 2013 bis 2017[8]

Grundlage eine zielgruppengerechte Ausgestaltung ihrer digitalen Vertriebskanäle vornehmen, die nicht länger ausschließlich auf Experteneinschätzungen oder theoretischen Erwartungen beruht sondern nun um empirische Erkenntnissen ergänzt wird.

Der Beitrag gliedert sich dabei wie folgt: Kapitel 4.2 strukturiert zunächst die breite Forschungslandschaft, gruppiert Beiträge zu Forschungssträngen und ordnet den Fokus der vorliegenden Arbeit in diese ein. Im Folgenden listet Kapitel 4.3 sowohl theoretische Modelle, die über die Adaption von Informationstechnologien aufklären, als auch relevante empirische Studien, welche die Eigenschaften von Online- bzw. Mobile-Banking Kunden untersuchen. In Kapitel 4.4 werden letztere sowohl kritisch diskutiert als auch übergreifende Erkenntnisse abgeleitet. Kapitel 4.5 fasst den vorliegenden Beitrag abschließend zusammen und beschreibt Fragestellungen für mögliche künftige Studien.

4.2 Forschungsstränge und Einordnung der Arbeit

Die wissenschaftliche Forschung hat bereits diverse Aspekte, die in Bezug zu Online-bzw. Mobile-Banking (nachfolgend OMB) stehen, untersucht. Akinci, Aksoy und Atilgan (2004) betrachten 38 Studien und

[8] Eigene Darstellung. Daten aus Statistisches Bundesamt (2018, S. 182 + 2018), Deutsche Bundesbank (2018, S. 4 ff.), Statistisches Bundesamt (2014 S. 172 + 203).

kategorisieren diese in die vier folgenden Gruppen, wobei Studien häufig mehrere Facetten betrachten und nicht immer eindeutig einer Gruppe zugeordnet werden können:[9]

1) Leistungen des Retail-Bankings
2) Distributionskanäle
3) Haltung und Betrachtungsweisen des Managements
4) Haltung der und Annahme durch Kunden

Literatur der Gruppen (1) und (2) stehen abseits des aktuellen Beitrags und werden daher nicht thematisiert. Studien der Gruppe (3) hinterfragen unter anderem, welche Auswirkungen aus dem Angebot bzw. der kundenseitigen Nutzung von OMB auf Kosten und Erträge der Bank resultieren. Diverse Analysen kommen dabei zu dem Ergebnis, dass die Profitabilität der Bank durch OMB gesteigert werden kann.[10] Wenngleich einige Untersuchungen einen kurzfristigen Ertragsrückgang feststellen,[11] dokumentieren andere mittel- bis langfristig eine Ertragssteigerung. Zum einen resultiert dies aus Möglichkeiten der Kostenreduktion.[12] Zum anderen begründet sie sich kundenseitig in einer höheren Produktnutzung[13] sowie Reduktion der Abwanderungswahrscheinlichkeit,[14] was wiederum den Kundenwert (Customer-Lifetime-Value) steigert.[15]
Beiträge der Gruppe (4), welche innerhalb der vorliegenden Arbeit diskutiert werden, untersuchen Eigenschaften der Nutzer, die zu einer Annahme (Nutzung) oder Ablehnung (Nicht-Nutzung) von OMB führen. Neben den technischen Möglichkeiten, die in den jeweiligen Vertriebskanälen vorgehalten werden, sind Wünsche, Erwartungen und Bedürfnisse der Kunden unterschiedlich und wesentlich für die Kanalwahl.[16] Die Anzahl dieser Studien ist dabei sehr beachtlich. Montazemi und Qahri-Saremi (2015) erstellen eine Meta-Analyse mit dem Fokus der Online-Banking Nutzung. Die Autoren finden insgesamt 332 Primärstudien, von denen nach Anwendung einiger Ausschlusskriterien 81 empirische Studien einbezogen werden konnten. Nejad (2016) visualisiert und diskutiert Studien zu finanzwirtschaftlichen Innovationen und findet hierzu 121 Beiträge, welche in den Jahren 1990 bis 2015 publiziert wurden. Aufgrund dieses sehr hohen Literaturumfangs ist eine weitere Unterteilung notwendig, um die Struktur der vorliegenden Forschungslandschaft verstehen zu können. Hanafizadeh, Keating und Khedmatgozar (2014) adaptieren hierzu die

[9] Vgl. Akinci, Aksoy und Atilgan (2004, S. 213 ff.).

[10] Vgl. Liu, Abhishek und Li (2017, S. 34), Tunay, Tunay und Akhisar (2015, S. 367), Gensler, Leeflang und Skiera (2012, S. 197), Ciciretti, Hasan und Zazzara (2009, S. 89), Acharya, Kagan und Lingam (2008, S. 434), Hernando und Nieto (2007, S. 1097), DeYoung, Lang und Nolle (2007, S. 1051).

[11] Vgl. Carlin, Olafsson und Pagel (2017, S. 4), Campbell und Frei (2010, S. 17).

[12] Vgl. Gensler, Leeflang und Skiera (2012, S. 197), Xue, Hitt und Chen (2011, S. 305), Hernando und Nieto (2007, S. 1088).

[13] Vgl. Xue, Hitt und Harker (2007, S. 31), Simon (2005, S. 141).

[14] Vgl. Xue, Hitt und Chen (2011, S. 302), Lambrecht (2005 S. 134).

[15] Vgl. Lambrecht (2005, S. 172), Simon (2005, S. 137).

[16] Vgl. Albesa (2007, S. 490).

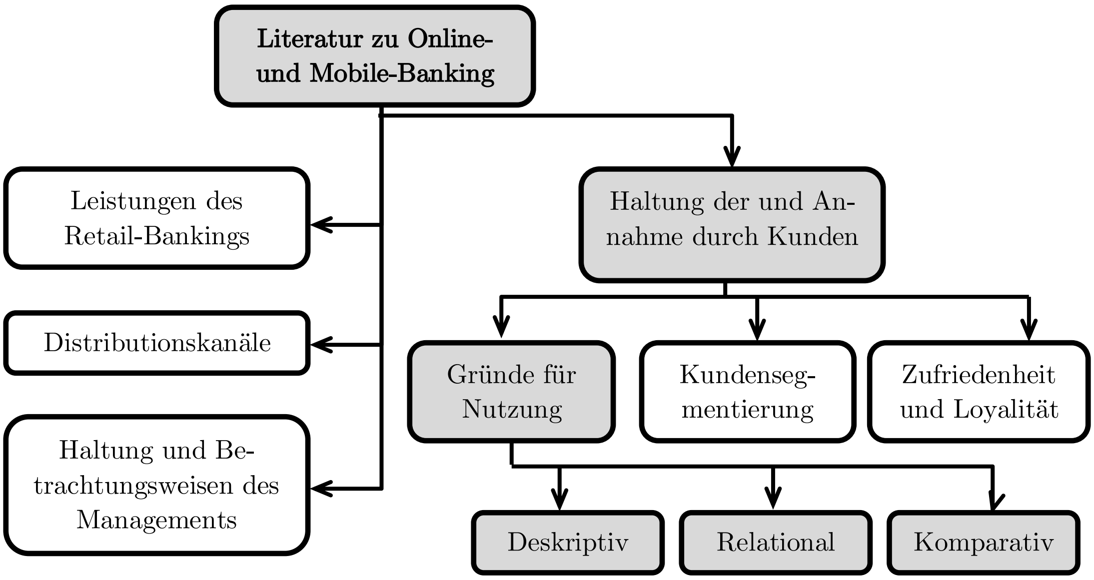

Abbildung C-2: Systematisierung der Online-Banking Literatur – Fokus: Gründe für Annahme durch Kunden[17]

zuvor dargestellten Literaturgruppen von Akinci, Aksoy und Atilgan (2004) und konkretisieren die Gruppe der Kundenperspektive über zwei weitere Unterebenen (siehe Abbildung C-2). Die erste jener Konkretisierungsebenen unterteilt die Literatur zur Kundenperspektive in drei Dimensionen. Literatur im Bereich „Gründe für Nutzung" stehen zu Beginn und analysieren Faktoren, die zu einer Nutzung von OMB führen.[18] Diese Studien berichten Einblicke zu Eigenschaften und Charakteristika der Nutzer, stehen im Fokus der vorliegenden Arbeit und werden nachstehend detailliert betrachtet. Die zweite Kategorie „Kundensegmentierung" beinhaltet die Analysen, welche anschließend versuchen aufgrund des Kanalnutzungsverhaltens Kundensegmente zu bilden und eine zielgerichtete

Betreuung zu gewährleisten. Abschließend gehören zur dritten Gruppe „Kundenzufriedenheit und Loyalität" die Beiträge, welche die Auswirkungen von OMB-Nutzung auf die Zufriedenheit und Loyalität der Kunden untersuchen. Wie zuvor dargestellt lassen sich hier positive Effekte ermitteln, welche u.a. den Kundenwert erhöhen.[19] Auch an dieser Stelle wird der Bedarf nach einer systematischen Auseinandersetzung mit dem Literaturkörper „Gründe für Nutzung" deutlich, da er gleichzeitig die Basis für die Gruppen „Kundensegmentierung" sowie „Zufriedenheit und Loyalität" bildet. Hinreichende Informationen aus dem ersten Bereich lassen fundierte Konzepte in den anderen beiden Gruppen zu und verhindern Fehleinschätzungen.

Hanafizadeh, Keating und Khedmatgozar (2014) systematisieren in ihrem Beitrag die in der ersten Gruppe „Gründe für Nutzung" vorliegende Literatur über eine zweite Ebene und betrachten hierzu insgesamt 165

[17] Eigene Darstellung, in Anlehnung an Hanafizadeh, Keating und Khedmatgozar (2014, S. 494).

[18] Vgl. Hanafizadeh, Keating und Khedmatgozar (2014, S. 494).

[19] Vgl. Hanafizadeh, Keating und Khedmatgozar (2014, S. 494).

Quellen, die bis zum Jahr 2012 erschienen sind.[20] Sie gelangen zu der Erkenntnis, dass sich diese Ausführungen in drei weitere Kategorien untergliedern lassen, welche ebenfalls in Abbildung C-2 dargestellt sind. Die deskriptiven Studien suchen nach den Eigenschaften von Kunden, die entweder zu einer Nutzung führen oder auch Barrieren darstellen und Kunden von einer Adaption abhalten. Es werden regelmäßig demographische (Alter, Geschlecht, Einkommen etc.) und auch psychologische Faktoren (Risikoempfinden, Preisbewusstsein, Effizienz etc.) untersucht.[21] In diesem Kontext wird jedoch nicht versucht, die einzelnen Variablen miteinander in Verbindung zu setzen, um auf dieser Grundlage ein theoretisches Modell zu entwickeln. Im Gegensatz zu den deskriptiven Studien versuchen die Relationalen zu verstehen, inwieweit die einzelnen Faktoren zusammenspielen und sich gegenseitig bedingen.[22] Dazu werden häufig die im folgenden Abschnitt dargestellten Modelle aus der Sozialpsychologie genutzt, um das Kundenverhalten theoretisch erklären zu können. Die empirischen Untersuchungen in diesem Bereich instrumentalisieren regelmäßig multivariate Verfahren, um den wissenschaftlichen Erkenntnisgewinn zu fördern. Dies ist bei den deskriptiven Studien in der Regel nicht gegeben.

Die dritte und letzte Gruppe bilden die komparativen Studien. Diese untersuchen OMB Nutzung und vergleichen wesentliche Attribute. Die Autoren betrachten dabei, ob Unterschiede in demographischen, kulturellen, technologischen oder politischen Aspekten zu einer unterschiedlichen OMB Nutzung führen. Teilweise geschieht dies, indem Datensamples in unterschiedlichen Ländern gebildet und die Nutzung miteinander verglichen wird. Andere Studien vergleichen wiederum die Nutzung von Vertriebskanälen miteinander. Hier steht z.B. die Fragestellung, ob die Kanäle Filiale, Telefon-Banking, Online-Banking, Mobile-Banking etc. in unterschiedlicher Intensität oder mit abweichender Motivation genutzt werden, im Vordergrund. Ferner existieren Studien, welche die Modelle der relationalen Studien miteinander vergleichen, um zu erfahren, ob bestimmte Modelle (der Sozialpsychologie) eine bessere Vorhersagekraft als andere besitzen.

4.3 Darstellung ausgewählter Forschungsbeiträge

4.3.1 Modelle zur theoretischen Erklärung

Zur theoretischen Erklärung von Faktoren, die einen Menschen zur Nutzung einer neuen Technologie bewegen, werden häufig Modelle der Sozialpsychologie verwendet. Besonders regelmäßig finden sich dabei die Nachstehenden, welche im Folgenden möglichst kurz beschrieben werden sollen:

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[20] Vgl. Hanafizadeh, Keating und Khedmatgozar (2014, S. 506).

[21] Vgl. Akinci, Aksoy und Atilgan (2004, S. 216 ff.), Hanafizadeh, Keating und Khedmatgozar (2014, S. 495).

[22] Vgl. Hanafizadeh, Keating und Khedmatgozar (2014, S. 496).

- Technology Acceptance Model (TAM) von Davis (1989)
- Diffusion of Innovation Model (IDT) von Rogers (1983)
- Unified Theory of User Acceptance of Technology (UTAUT) von Venkatesh et al. (2003)

Das TAM definiert die beiden Faktoren *empfundene Nützlichkeit* sowie *empfundene Einfachheit* als maßgeblich für die Adaption einer Informationstechnologie.[23] Das IDT postuliert, dass im Zeitverlauf unterschiedliche Nutzergruppen eine Innovation annehmen. Zu Beginn stehen die *Innovatoren*, gefolgt von den *frühen Nutzern*, der *frühen Mehrheit*, *späten Mehrheit* bis hin zu den *Nachzüglern*.[24] Wesentlich für die Zuordnung eines (potentiellen) Nutzers zu einer der Kategorien sind drei Dimensionen: Die Erste wird als *relativer Vorteil* bezeichnet und ist mit der *empfundenen Nützlichkeit* aus dem TAM vergleichbar. Die Zweite lautet *Komplexität* und bildet das Gegenstück zu *empfundene Einfachheit*. Die dritte und letzte Kategorie heißt *Kompatibilität* und beschreibt den Grad der Veränderung bzw. das empfundene Risiko, welche die Nutzung der Technologie für ein Individuum bedeuten würde. Hier fließen auch Merkmale und Verhaltensweisen des sozialen Umfelds mit ein.[25]

Bei der Entwicklung des UTAUT wurden acht bestehende Modelle, welche alle versuchen die Annahme von Innovationen zu prognostizieren, verglichen und auf dieser Grundlage ein Neues gebildet. Bei diesem sind die Dimensionen *Leistungserwartung*, *Aufwandserwartung*, *Einfluss des sozialen Umfelds* sowie *organisatorische und technische Rahmenbedingungen* ausschlaggebend für die Nutzung bzw. Ablehnung. Es finden sich erneut Parallelen zu den zuvor dargestellten Modellen TAM und IDT. Die genannten vier Dimensionen werden teilweise durch die Eigenschaften *Alter*, *Geschlecht*, *persönliche Erfahrungen* und *Freiwilligkeit der Nutzung* beeinflusst.

Mit Blick auf die empirische Forschungslandschaft lässt sich feststellen, dass sehr viele Beiträge die Erklärungsgüte jener Modelle überprüfen und häufig auch gute Ergebnisse produzieren. Insbesondere das TAM ist wohl das meist genutzte Modell in der Online- bzw. Mobile-Banking Forschung.[26] Durch dieses lässt sich im Mittel rund 40% der beobachteten Varianz erklären. Nach Anpassungen werden teilweise noch bessere Ergebnisse erzielt.[27] Obige Modelle eignen sich demnach zur Ermittlung der Faktoren, die zu OMB Nutzung führen und sollen daher auch zur Klassifikation von Einflussgrößen im nächsten Kapitel dienen.

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[23] Vgl. Davis (1989, S.323).

[24] Vgl. Rogers (1983, S. 269).

[25] Vgl. Rogers (1983, S. 269), Montazemi und Qahri-Saremi (2015, S. 211).

[26] Vgl. Sangle und Awasthi (2011, S. 900), Pikkarainen et al. (2004, S. 226), Khasawneh (2015, S. 3).

[27] Vgl. Koenig-Lewis, Palmer und Moll (2010, S. 410), die bei einem relativ kleinen Sample rund 65% der beobachteten Varianz erklären können.

4.3.2 Ergebnisse empirischer Studien

Zur Identifikation von Analysen, die Faktoren der OMB Adaption erforschen, dienten primär die Datenbanken *Business Source Premier, SSRN* sowie *Google Scholar.* Als Suchbegriffe wurden „Online-Banking", „Mobile-Banking", „Multi-Kanal" und „Multi-Channel" verwendet. In den gefundenen Studien wurden außerdem die Literaturverzeichnisse auf weitere relevante Beiträge überprüft. Abschließend wurden die Konferenzprogramme international anerkannter Verbände auf relevante Inhalte untersucht.[28]

Um Erkenntnisse für den deutschen Markt ableiten zu können, wurde anschließend eine Eingrenzung vorgenommen. Grund hierfür ist, dass von Unterschieden in der Nutzung von Online- bzw. Mobile-Banking bei Menschen unterschiedlicher Nationalitäten auszugehen ist. Verschiedene Reifegrade des Finanzdienstleistungssektors, heterogene Ausbaustufen der technischen Infrastruktur, kulturelle Unterschiede uvm. können in differierenden Nutzungsstrukturen in unterschiedlichen Ländern resultieren. Dies führt u.a. dazu, dass in Amerika 45% der Internetnutzer auch Online-Banking einsetzen, in Europa knapp 38% (wobei in Nordeuropa eine höhere Nutzungsquote als im Süden besteht) und in Afrika lediglich ca. 9%.[29] Sayar und Wolfe (2007) vergleichen Online-Banking Nutzer aus der Türkei und Großbritannien, Li und Kirkup (2007) Nutzer aus China und Großbritannien. Beide kommen, bedingt durch die Nationalität, zu abweichenden Verhaltensmustern. Geert Hofstede hat den Uncertainty-Avoidance-Index entwickelt, der in diversen Forschungsbereichen, u.a. im Personalwesen oder im Controlling, genutzt wird.[30] Dieser misst die Reaktion verschiedener Kulturen auf Unsicherheit. So erhält z.B. Deutschland 65 Punkte, Singapur hingegen nur Acht.[31] Menschen aus Singapur gehen demnach im Vergleich zu Einwohnern Deutschlands viel entspannter mit Unsicherheit um. Es ist davon auszugehen, dass sich dies auch in der Nutzung von Online- bzw. Mobile-Banking (z.B. im Hinblick auf Sicherheitsbedenken) widerspiegelt. Vor diesem Hintergrund fokussiert sich Tabelle C-2 auf Studien, welche in Europa oder den USA erstellt wurden. Diese listet zunächst in Abschnitt (A) die Untersuchungen, welche auf einem theoretischen Modell aus Kapitel 4.3.1 oder einem Vergleichbaren aufbauen. Abschnitt (B) zeigt die Studien, welche kein solches Modell zugrunde legen sondern basierend auf anderen Hypothesen Variablen auswählen und signifikante Einflüsse überprüfen.

[28] Beispielsweise wurden die Konferenzprogramme der American Finance Association, European Finance Association, European Retail Investment Conference und Western Finance Association seit 2010 betrachtet.

[29] Vgl. Montazemi und Qahri-Saremi (2015, S. 210), Gumsheimer, Hecker und Krüger (2015).

[30] Vgl. Merchant und Van der Stede (2007, S. 749).

[31] Vgl. Hofstede (2010).

Studie **Kategori-sierung**	**Untersuchte Plattform(en)**	**Allgemeine Merkmale der Studie** L = Land M = Verwendetes Modell S = Form der Samplegenerierung N = Anzahl Datensätze V = Verfahren zur Datenanalyse A = Untersuchte abhängige Variable	**Ergebnisse** Welche unabhängigen Variablen (Determinanten) nehmen signifikanten Einfluss? + Positiver Einfluss – Negativer Einfluss Determinanten ohne signifikanten Einfluss werden nicht berücksichtigt.
Abschnitt (A): Studien auf Grundlage eines theoretischen Modells			
Liu, Abhishek und Li (2017) Komparativ	Mobile-Banking	L = USA M = Eigenes Modell S = Nutzungsdaten N = 194.493 V = Regressionsanalyse A = Proband nutzt Mobile-Banking (Ja/Nein, unterteilt in Smartphone und Tablet)	Smartphone-Banking – Einkommen + Tablet-Banking + Dauer Geschäftsbeziehung + Anzahl Transaktionen – Kontosaldo – Anzahl GAA in PLZ-Gebiet Tablet-Banking + Einkommen + Smartphone-Banking – Dauer Geschäftsbeziehung + Anzahl Transaktionen + Kontosaldo + Anzahl GAA in PLZ-Gebiet
Montazemi und Qahri-Saremi (2015) Relational	Online-Banking	L = International M = IDT S = Analyse von 81 Primärstudien N = 25.265 V = Meta-Analyse A = (1) Absicht Online-Banking erstmalig zu nutzen und (2) Absicht Online-Banking dauerhaft zu nutzen	+ Empfundene Nützlichkeit + Empfundene Einfachheit + Vertrauen in Online-Banking sowie in die physische Bank + Sicherheit der Plattform + Einfluss durch soziales Umfeld [Nur bei (1)] + Qualität der Infrastruktur, der dargestellten Informationen sowie der Bearbeitung von Serviceanfragen [Nur bei (2)]

Lambrecht, Seim und Tucker (2011) Relational	Online-Banking	L = Deutschland M = Eigenes Modell S = Nutzungsdaten N = 2.130 V = Regressionsanalyse A = Nutzung von Online-Banking (Ja/Nein)	+ Geschlecht (Männer) + Filiale in der Nähe + Summe der Transaktionen in Offline-Kanälen + Transaktion im Vormonat – Alter + Ferien und Feiertage während des Anmeldungsprozesses
Saeed (2011) Relational	Mobile-Banking	L = USA M = Eigenes Modell, basierend auf UTAUT und IDT S = Fragebogen N = 223 V = Diskriminanzanalyse A = Nutzung von Mobile-Banking (Ja/Nein)	+ Zugänglichkeit – Aufmerksamkeit + Einfachheit der Navigation
Koenig-Lewis, Palmer und Moll (2010) Relational	Mobile-Banking	L = Deutschland M = Eigenes Modell, basierend auf TAM und IDT S = Fragebogen N = 155 V = Strukturgleichungsmodell A = Absicht Mobile-Banking zu nutzen	+ Geschlecht (Männer) + Empfundene Nützlichkeit + Kompatibilität zu eigenen Werten – Wahrgenommenes Risiko Vertrauen, Glaubwürdigkeit und Empfundene Einfachheit nehmen indirekt Einfluss

Luo, Li und Shim (2010) Relational	Mobile-Banking	L = USA M = Eigenes Modell S = Fragebogen N = 122 V = Strukturgleichungsmodell A = Absicht Mobile-Banking zu nutzen	+ Erwartete Leistungsfähigkeit – Wahrgenommenes Risiko
Schierz, Schilke und Wirtz (2010) Relational	Mobile-Payment	L = Deutschland M = Eigenes Modell, basierend auf dem TAM S = Fragebogen N = 1.447 V = Strukturgleichungsmodell A = Absicht Mobile-Payment zu nutzen (Ja/Nein)	+ Kompatibilität zu eigenen Werten + Einfluss durch soziales Umfeld + Mobilität im Alltag
Albesa (2007) Deskriptiv / Komparativ	Filiale (FIL), Geldausgabeautomaten (GAA), Online-Banking (OB)	L = Spanien M = Eigenes Modell S = Fragebogen N = 400 V = Konfirmatorische Faktorenanalyse A = Proband nutzt Online-Banking (Ja/Nein)	– Wunsch nach sozialem Kontakt + Kenntnis der Funktionsweise von GAA und/oder OB + Zufriedenheit mit GAA und/oder OB

Falk et al. (2007) Relational	Filiale (FIL), Online-Banking (OB)	L = Deutschland M = Eigenes Modell, basierend auf dem TAM S = Fragebogen N = 639 Bankkunden V = Strukturgleichungsmodell A = Absicht Online-Banking zu nutzen	– Zufriedenheit mit dem Filialservice
Xue, Hitt und Harker (2007) Relational / Komparativ	Filiale (FIL), Sowie die Self-Service-Technology (SST) Kanäle: Geldausgabeautomaten, Online-Banking (OB), Sprachcomputer (SC)	L = USA M = Eigenes Modell S = Nutzungsdaten N = 25.000 Bankkunden V = Regressionsanalyse A = Messung der kundenindividuellen Effizienz und deren Auswirkung auf (1) Kanalnutzung sowie (2) Profitabilität, Produktnutzung und Loyalität	Zu (1) – Fokus auf OB – Alter + Bildung + Höhere Filialdichte + Einkommen + Haushalte, bei denen die Frau als Kontoinhaberin auftritt
Flavián, Guinalíu und Torres (2006) Relational	Online-Banking	L = Spanien M = Eigenes Modell S = Fragebogen N = 633 V = Regressionsanalyse A = Proband nutzt Online-Banking (Ja/Nein)	+ Vertrauen in die Filialbank + Geschlecht (Männer) + Einkommen – Alter
Curran und Meuter (2005) Relational / Komparativ	Geldausgabeautomaten (GAA), Online-Banking (OB), Telefon-Banking (TB)	L = USA M = Eigenes Modell, basierend auf dem TAM S = Fragebogen N = 215 (GAA), 206 (OB), 207 (TB) V = Strukturgleichungsmodell A = (1) Attitüde gegenüber einem Vertriebskanal und (2) die Absicht diesen zu nutzen.	Einfluss auf (1) + Einfachheit der Nutzung (GAA) + Empfundene Nützlichkeit (ATM, TB) – Wahrgenommenes Risiko (OB) Einfluss auf (2) – Attitüde (ATM, OB, TB)
Pikkarainen et al. (2004) Relational	Online-Banking	L = Finnland M = TAM, erweitert um diverse Faktoren S = Fragebogen N = 268 V = Regressionsanalyse A = Nutzung von Online-Banking	+ Einkommen + Empfundene Nützlichkeit + Kenntnis der Leistungsfähigkeit

Devlin und Yeung (2003) Relational	Online-Banking	L = (keine Angabe) M = Eigenes Modell S = Fragebogen N = 3.804 V = Regressionsanalyse A = Nutzung von Online-Banking	– Service in der Filiale + Zufriedenheit mit SB-Automaten + Geschlecht (Männer) + Höhere soziale Schicht – Alter + Einkommen + Bildung + Existenz anderer, direkter Vertriebskanäle
Abschnitt (B): Studien auf Basis alternativer Hypothesen			
Carlin, Olafsson und Pagel (2017) Deskriptiv	Mobile-Banking	L = Island M = / S = Nutzungsdaten N = 13.838 Kunden V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: – Alter – Einkommen – Ausgaben + Geschlecht (Männer) – Kontosaldo

Cope, Rock und Schmeiser (2013) Relational	Mobile-Banking	L = USA M = / S = Fragebogen N = 1.921 V = Regressionsanalyse A = Proband nutzt Mobile-Banking (Ja/Nein)	– Alter – Sicherheitsbedenken – Risikoaversion in Bezug auf Geldanlage + Besitz eines Smartphones • Unterschiede zwischen Ethnien vorhanden
Gensler, Leeflang und Skiera (2012) Relational	Online-Banking	L = Europa M = / S = Nutzungsdaten N = 86.754 V = Regressionsanalyse A = Proband nutzt Online-Banking (Ja/Nein)	– Alter – Dauer Kundenbeziehung + Gemeinschaftskonto + Besitz eines Girokontos + Besitz einer Kreditkarte
Laukkanen und Cruz (2012) Komparativ	Mobile-Banking	L = Portugal und Finnland M = / S = Fragebogen N = 3.582 V = Regressionsanalyse A = Proband nutzt Mobile-Banking (Ja/Nein)	+ Geschlecht (Männer) + Erfahrungen mit anderen Mobile-Services + Land (Portugal im Vergleich zu Finnland) + Smartphone (im Vergleich zu einem Standard-Mobiltelefon) + Kulturelle Attribute (Individualität, Langfristorientierung, Maskulinität)
Xue, Hitt und Chen (2011) Deskriptiv / Komparativ	Filiale (FIL), Geldausgabeautomaten (GAA), Online-Banking (OB), Call-Center (CC), Sprachcomputer (SC)	L = USA M = / S = Nutzungsdaten N = 28.945 V = Regressionsanalyse A = Nutzung von Online-Banking (Ja/Nein)	+ Anzahl Transaktionen – Alter + Bildung + Anzahl Online-Banking Kunden in der gleichen geografischen Region
Campbell und Frei (2010) Deskriptiv / Komparativ	Filiale (FIL), Call-Center (CC), Geldausgabeautomaten (GAA), Online-Banking (OB), Sprachcomputer (SC)	L = USA M = / S = Nutzungsdaten N = 200.000 Kunden V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: – Alter – Dauer der Geschäftsbeziehung + Produktnutzung + Kontosaldo + Kundenprofitabilität

Laukkanen und Pasanen (2008) Deskriptiv	Mobile-Banking	L = Finnland M = / S = Fragebogen N = 2.675 V = Regressionsanalyse A = Nutzung von Mobile-Banking	• Alter (Mittleres Alter am stärksten) + Geschlecht (Männer)
Berger und Gensler (2007) Deskriptiv	Online-Banking	L = Deutschland M = / S = Fragebogen N = 19.119 V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: – Alter + Einkommen + Bildung + Interesse an Bankprodukten + Nutzung von Zahlungsverkehrsprodukten (inkl. Kreditkarte)

Lambrecht (2005) Deskriptiv	Online-Banking	L = Deutschland M = / S = Nutzungsdaten N = Für (1) 22.158 bzw. für (2) 952 Kunden V = Regressionsanalyse A = Welche Faktoren führen zur (1) Anmeldung für Online-Banking bzw. (2) aktiven Nutzung?	Für beide Untersuchungsszenarien wurden folgende Ergebnisse ermittelt: – Alter + Durchschnittliche Transaktionsanzahl
Simon (2005) Deskriptiv	Online-Banking	L = Deutschland M = / S = Nutzungsdaten N = 10.321 V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: – Alter + Geschlecht (Männer) – Dauer Geschäftsbeziehung
Mattila (2003) Deskriptiv	Mobile-Banking	L = Finnland M = / S = Fragebogen N = 1.253 V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: + Geschlecht (Männer) + Alter (Mittleres Alter am stärksten) + Verheiratet + Bildung + Einfluss durch soziales Umfeld
Hitt und Frei (2002) Deskriptiv	Online-Banking	L = USA M = / S = Stichtagsbezogene Nutzungsdaten von Kunden vier unterschiedlicher Banken N = 687.283 Kunden V = Deskriptive Statistik A = /	Basierend auf deskriptiver Statistik: + Einkommen – Alter + Verheiratet + Hausbesitzer + Produktnutzung + Kontosalden + Kundenprofitabilität

Tabelle C-2: Darstellung aller betrachteten Studien

4.4 Kritische Würdigung der bisherigen Forschungslandschaft

4.4.1 Betrachtete Vertriebskanäle

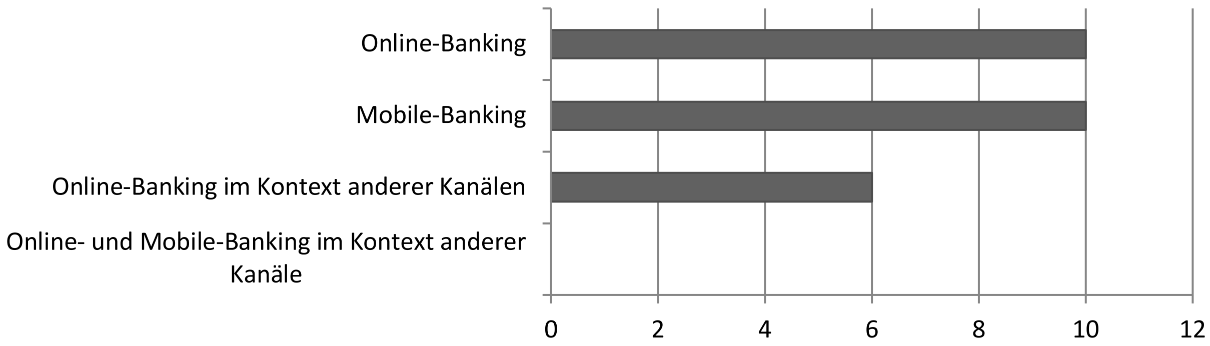

Abbildung C-3: Untersuchungsgegenstand der betrachteten Studien

Untersuchungsgegenstand	Studien
Online-Banking	10 Studien Montazemi und Qahri-Saremi (2015), Gensler, Leeflang und Skiera (2012), Lambrecht, Seim und Tucker (2011), Berger und Gensler (2007), Flavián, Guinalíu und Torres (2006), Lambrecht (2005), Simon (2005), Pikkarainen, et al. (2004), Devlin und Yeung (2003), Hitt und Frei (2002)
Mobile-Banking	10 Studien Carlin, Olafsson und Pagel (2017), Liu, Abhishek und Li (2017), Cope, Rock und Schmeiser (2013), Laukkanen und Cruz (2012), Saeed (2011), Schierz, Schilke und Wirtz (2010), Luo, Li und Shim (2010), Koenig-Lewis, Palmer und Moll (2010), Laukkanen und Pasanen (2008), Mattila (2003)
Online-Banking im Kontext anderer Kanälen	6 Studien Xue, Hitt und Chen (2011), Campbell und Frei (2010), Xue, Hitt und Harker (2007), Albesa (2007), Falk, et al. (2007), Curran und Meuter (2005),
Online- und Mobile-Banking im Kontext anderer Kanäle	Keine Studie
Gesamt	26 Studien

Tabelle C-3: Untersuchungsgegenstand der betrachteten Studien

Der Literaturüberblick in Tabelle C-2 stellt Determinanten vor, die im europäischen bzw. US-amerikanischen Raum zu einer Nutzung von OMB führen. Hierzu wurden insgesamt 26 Studien integriert. Abbildung C-3 und Tabelle C-3 unterteilen die Studien im Hinblick auf deren Untersuchungsgegenstand. Es wird deutlich, dass sich die Meisten isoliert mit Aspekten des Online- bzw. Mobile-Bankings beschäftigen. Sechs betrachten Online-Banking im Kontext mit anderen Kanälen (hauptsächliche Geldausgabeautomaten, Filialen und Telefon-Banking). Leider konnte keine einzige Analyse gefunden werden, welche Online- und Mobile-Banking im Kontext mit anderen Kanälen untersucht. Diese wären jedoch wichtig, da die meisten

Banken in Deutschland einen vollwertigen Multi-Kanal-Vertrieb aufgebaut haben und OMB somit in der Regel nicht isoliert angeboten wird. Die Literaturlandschaft ist daher mit 26 Studien zwar umfangreich jedoch nicht abschließend und bietet Raum für Untersuchungen, die Multi-Kanal-Vertrieb vollständig beobachten.

4.4.2 Form der Samplegenerierung und des Analyseverfahrens

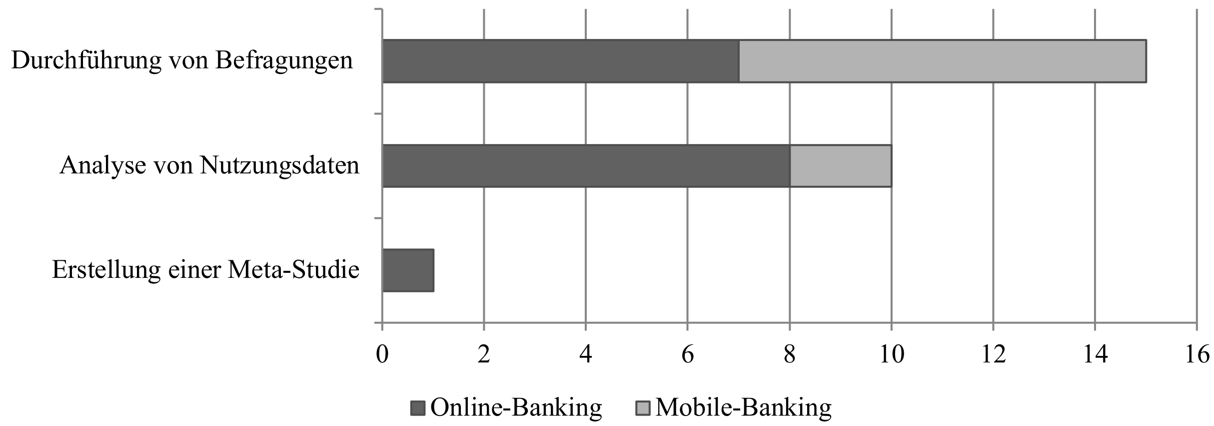

Abbildung C-4: Form der Samplegenerierung in den betrachteten Studien

Samplegenerierung	Anzahl Studien Online-Banking	Anzahl Studien Mobile-Banking
Durchführung von Befragungen	7 Studien Albesa (2007), Berger und Gensler (2007), Falk, et al. (2007), Flavián, Guinalíu und Torres (2006), Curran und Meuter (2005), Pikkarainen, et al. (2004), Devlin und Yeung (2003)	8 Studien Cope, Rock und Schmeiser (2013), Laukkanen und Cruz (2012), Saeed (2011), Koenig-Lewis, Palmer und Moll (2010), Luo, Li und Shim (2010), Schierz, Schilke und Wirtz (2010), Laukkanen und Pasanen (2008), Mattila (2003)
Analyse von Nutzungsdaten	8 Studien Gensler, Leeflang und Skiera (2012), Lambrecht, Seim und Tucker (2011), Xue, Hitt und Chen (2011), Campbell und Frei (2010), Xue, Hitt und Harker (2007), Lambrecht (2005), Simon (2005), Hitt und Frei (2002)	2 Studien Carlin, Olafsson und Pagel (2017), Liu, Abhishek und Li (2017)
Erstellung einer Meta-Studie	1 Studie Montazemi und Qahri-Saremi (2015)	Keine Studie
Gesamt	16 Studien	10 Studien

Tabelle C-4: Form der Samplegenerierung in den betrachteten Studien

zeigen, wie die beobachteten Studien ihre jeweilige Datengrundlage erhoben haben. Es fällt auf, dass die Meisten zur Untersuchung der Faktoren, welche zu einer Annahme von OMB führen, Fragebögen als Datengrundlage verwenden.[32] Auch wenn die Befragungen unterschiedlich durchgeführt wurden (Brief, Internet, E-Mail, Telefon, Mensch-zu-Mensch o.ä.) handelt es sich immer um eine Selbsteinschätzung. Jene Form der Sample-Bildung weist zum Teil erhebliche Nachteile auf: In einer Untersuchung von Deutsche Bank Research (2010) wurden Kunden zu Informationsbeschaffung im Internet befragt. 3% der Bankkunden gaben an, sich vor einem Produktkauf im Internet informiert zu haben. Da parallel zu der Befragung eine Software auf dem PC installiert war, konnte das tatsächliche Nutzungsverhalten untersucht werden. Bei Betrachtung dieser Daten wurde festgestellt, dass entgegen der Aussagen nicht nur 3% sondern insgesamt 48,6% der Probanden zuvor online recherchiert haben.[33] Es wird deutlich, wie erheblich Aussagen bei einer Nutzerbefragung von der Realität abweichen können. Auch Xue, Hitt und Chen (2011, S. 293) und Liu, Abhishek und Li (2017, S. 3) gehen auf diese Problematik ein und verweisen darauf, dass bei Selbsteinschätzung mit Verzerrungen zu rechnen ist.

Erfreulicherweise operationalisieren zehn der 26 Studien tatsächliche Nutzungsdaten und berichten über Eigenschaften der Online- bzw. Mobile-Banking Kunden. Acht dieser zehn Studien fokussieren Online-Banking. Im Bereich des Mobile-Bankings konnten mit Carlin, Olafsson und Pagel (2017) sowie Liu, Abhishek und Li (2017) zwei Studien benannt werden, die auf Basis von Nutzungsdaten Aussagen zu Eigenschaften von Mobile-Banking Kunden treffen. Erstere berichtet deskriptiv Eigenschaften der Nutzer und keine multivariate Analyse, wobei eine solche die zur Nutzung führenden Faktoren genauer identifizieren könnte. Montazemi und Qahri-Saremi (2015) betrachten Online-Banking und führen hierzu eine Meta-Analyse durch.

Somit ist zu resümieren, dass die bestehende Literaturlandschaft im Hinblick auf Online-Banking bereits vielseitige Einblicke gewährt. Bei Mobile-Banking hingegen ist zum einen die Erstellung weiterer multivariater Studien auf Grundlage von Nutzungsdaten und zum anderen die Durchführung von Meta-Studien erstrebenswert.

4.4.3 Übereinstimmend gefundene Ergebnisse

Tabelle C-2 zeigt neben einer Vielzahl von Studien auch eine Vielzahl unterschiedlicher Ergebnisse. 14 der insgesamt 26 Analysen basieren entweder auf einem der theoretischen Modelle aus Abschnitt 4.3.1 oder weisen eine hohe Ähnlichkeit zu diesen auf. Die übrigen 12 Analysen lassen kein theoretisches Modell erkennen sondern fundieren ihre Studie auf anderweitig generierten Hypothesen. Diese vielfältigen Untersuchungsdesigns lassen erkennen, dass diverse Möglichkeiten existieren, um die Eigenschaften von OMB Kunden zu untersuchen. Der vorliegende Beitrag richtet sich an Entscheider aus Banken und soll daher

[32] Akinci, Aksoy und Atilgan (2004, S. 220 f.) kommen ebenfalls zu dieser Einschätzung.

[33] Vgl. Deutsche Bank Research (2010, S. 6).

insbesondere die Konstrukte fokussieren, welche einer Bank in der Regel bekannt sind.[34] Während Einflussfaktoren wie z.B. *empfundene Nützlichkeit* oder *empfundene Einfachheit* typischerweise nicht im Datenbestand eines Finanzdienstleisters erfasst werden ist dies bei soziodemografischen Daten in weiten Teilen gegeben. Bei soziodemografischen Daten handelt es sich um Angaben zur Person wie z.B. Alter, Geschlecht, Nationalität etc.[35] Wan, Luk und Chow (2005, S. 268) zeigen, dass soziodemografische Daten einen hohen Erklärungsgehalt hinsichtlich der Wahl des bevorzugten Vertriebskanals haben und sich somit gut für solche Analysen eignen. Darüber hinaus liegen der Bank auch Angaben zur Dauer der Kundenbeziehung, Produktnutzung, Kontosalden, Transaktionsdaten etc. vor, die ebenfalls von diversen Studien genutzt werden.[36] Wenn Aspekte wie Vertrauen oder Zufriedenheit über alternative Instrumente, wie z.B. *räumliche Nähe* oder *Regelmäßigkeit der Nutzung,* gemessen wurden, fanden diese ebenfalls Eingang in die nachstehenden Ausführungen.

Abbildung C-5 und Tabelle C-5 untersuchen die Studien aus Tabelle C-2 und fokussieren die signifikanten Ergebnisse, die zu soziodemografischen und weiteren, der Bank vorliegenden Daten generiert werden konnten. Wesentlichen Einfluss nimmt in vielen Studien das *Alter* des Probanden. Dieses korreliert in Bezug auf Online-Banking in allen Beiträgen negativ zu der Entscheidung die Technologie zu nutzen. Dies bedeutet, dass Online-Banking Nutzer tendenziell jüngere Menschen sind. Die Analysen mit Fokus auf Mobile-Banking zeigen leicht abweichende Ergebnisse: Bei den Meisten weisen insbesondere Kunden in den mittleren Alterssegmenten (zwischen 35 und 45 Jahre) die höchsten Nutzungszahlen auf.[37] Abbildung C-5 veranschaulicht dies durch eine mittig zur x-Achse positionierte Säule. Lediglich Mattila (2003) konstatiert, dass die Mobile-Banking Nutzung bei jungen Kunden im Alter zwischen 25 und 34 am stärksten ausgeprägt ist.

Identischen Einfluss nehmen die Variablen: *Anzahl Transaktionen*, *Beziehungsstatus (verheiratet)*, *Bildungsgrad der Nutzer*, *Geschlecht (Männer)* sowie *Meinung/Nutzung des sozialen Umfelds*. Diese korrelieren alle positiv zur Entscheidung OMB zu nutzen. Lambrecht (2005, S. 125) postuliert ein Modell, welches lediglich die Kovariaten *Alter* und *Anzahl Transaktionen* integriert und hierüber die erstmalige Nutzung von Online-Banking mit einem R^2 von 14,7% erklärt. Dies zeigt den erheblichen Einfluss dieser Variablen auf die Entscheidung, Online-Banking einzusetzen. Die Messung der Variable *Meinung/Nutzung des sozialen Umfelds* ist für Banken nicht unmittelbar möglich. Xue, Hitt und Chen (2011, S. 301) instrumentalisieren die Anzahl aller Online-Banking Nutzer in einer bestimmten Postleitzahl und erreichen dadurch eine Annäherung über die Aufgeschlossenheit des sozialen Umfelds eines Probanden im Hinblick auf OMB. Darüber hinaus kann zumindest für Online-Banking festgestellt werden, dass Höhe der Kundenprofitabilität und

[34] Vgl. Lambrecht (2005, S. 108) für eine ähnliche Argumentation.

[35] Vgl. Meffert, Burmann und Kirchgeorg (2015, S. 698), Clemes, Gan und Du (2012, S. 37), Black, et al. (2002, S. 166).

[36] Vgl. Akinci, Aksoy und Atilgan (2004, S. 216 ff.), Buell, Campbell und Frei (2010, S. 686), Xue, Hitt und Chen (2011, S. 297), Clemes, Gan und Du (2012, S. 37), Izogo et al. (2012, S. 32), Hanafizadeh, Keating und Khedmatgozar (2014, S. 495).

[37] Vgl. Carlin, Olafsson und Pagel (2017, S. 30), Cope, Rock und Schmeiser (2013, S. 29), Laukkanen und Pasanen (2008, S. 92).

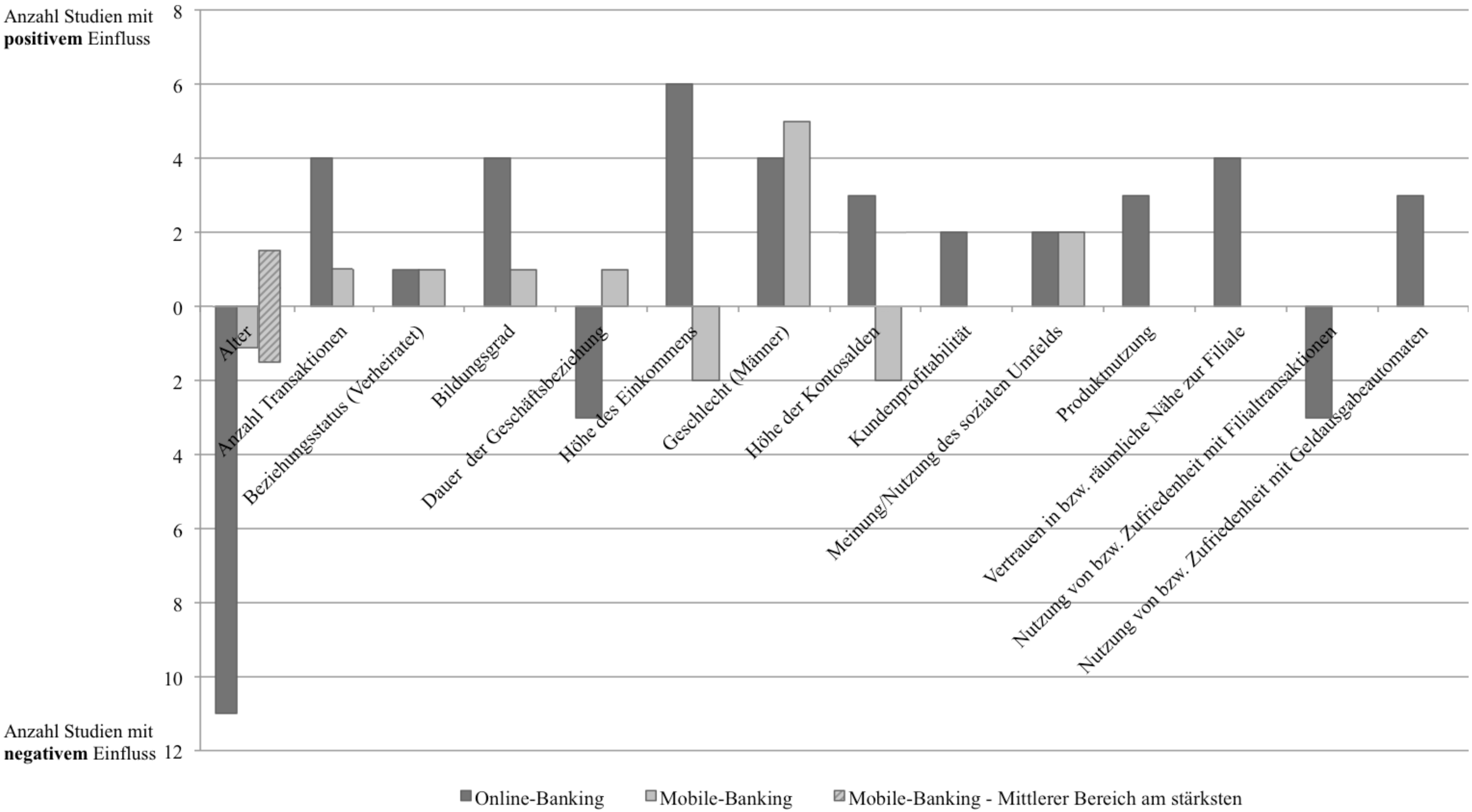

Abbildung C-5: Visualisierung der Faktoren, die Einfluss auf die Nutzung von Online- bzw. Mobile-Banking nehmen

Kundeneigenschaft	Korrelation Online-Banking	Korrelation Mobile-Banking
Alter	**Positiv:** - **Mittlerer Bereich am stärksten:** - **Negativ:** Gensler, Leeflang und Skiera (2012), Lambrecht, Seim und Tucker (2011), Xue, Hitt und Chen (2011), Campbell und Frei (2010), Berger und Gensler (2007), Xue, Hitt und Harker (2007), Flavián, Guinalíu und Torres (2006), Lambrecht (2005), Simon (2005), Devlin und Yeung (2003), Hitt und Frei (2002)	**Positiv:** - **Mittlerer Bereich am stärksten:** Carlin, Olafsson und Pagel (2017), Cope, Rock und Schmeiser (2013), Laukkanen und Pasanen (2008) **Negativ:** Mattila (2003)
Anzahl Transaktionen	**Positiv:** Xue, Hitt und Chen (2011), Lambrecht, Seim und Tucker (2011), Lambrecht (2005), Hitt und Frei (2002) **Negativ:** -	**Positiv:** Liu, Abhishek und Li (2017) **Negativ:** -
Beziehungsstatus (Verheiratet)	**Positiv:** Hitt und Frei (2002) **Negativ:** -	**Positiv:** Mattila (2003) **Negativ:** -
Bildungsgrad	**Positiv:** Xue, Hitt und Chen (2011), Berger und Gensler (2007), Xue, Hitt und Harker (2007), Devlin und Yeung (2003) **Negativ:** -	**Positiv:** Mattila (2003) **Negativ:** -
Dauer der Geschäftsbeziehung	**Positiv:** - **Negativ:** Gensler, Leeflang und Skiera (2012), Campbell und Frei (2010), Simon (2005)	**Positiv:** Liu, Abhishek und Li (2017) **Negativ:** -
Höhe des Einkommens	**Positiv:** Berger und Gensler (2007), Xue, Hitt und Harker (2007), Flavián, Guinalíu und Torres (2006), Pikkarainen, et al. (2004), Devlin und Yeung (2003), Hitt und Frei (2002) **Negativ:** -	**Positiv:** - **Negativ:** Carlin, Olafsson und Pagel (2017), Liu, Abhishek und Li (2017)
Geschlecht (Männer)	**Positiv:** Lambrecht, Seim und Tucker (2011), Flavián, Guinalíu und Torres (2006), Simon (2005), Devlin und Yeung (2003) **Negativ:** -	**Positiv:** Carlin, Olafsson und Pagel (2017), Laukkanen und Cruz (2012), Koenig-Lewis, Palmer und Moll (2010), Laukkanen und Pasanen (2008), Mattila (2003) **Negativ:** -
Höhe der Kontosalden	**Positiv:** Campbell und Frei (2010), Devlin und Yeung (2003), Hitt und Frei (2002) **Negativ:**	**Positiv:** - **Negativ:** Carlin, Olafsson und Pagel (2017), Liu, Abhishek und Li (2017)
Kundenprofitabilität	**Positiv:** Campbell und Frei (2010), Hitt und Frei (2002) **Negativ:**	**Positiv:** - **Negativ:** -

Meinung/Nutzung des sozialen Umfelds	**Positiv:** Montazemi und Qahri-Saremi (2015), Xue, Hitt und Chen (2011) **Negativ:** -	**Positiv:** Schierz, Schilke und Wirtz (2010), Mattila (2003) **Negativ:** -
Produktnutzung	**Positiv:** Gensler, Leeflang und Skiera (2012), Berger und Gensler (2007), Hitt und Frei (2002) **Negativ:** -	**Positiv:** - **Negativ:** -
Vertrauen in bzw. räumliche Nähe zur Filiale	**Positiv:** Montazemi und Qahri-Saremi (2015), Lambrecht, Seim und Tucker (2011), Xue, Hitt und Harker (2007), Flavián, Guinalíu und Torres (2006) **Negativ:** -	**Positiv:** - **Negativ:** -
Nutzung von bzw. Zufriedenheit mit Filialtransaktionen	**Positiv:** - **Negativ:** Albesa (2007), Falk, et al. (2007), Devlin und Yeung (2003)	**Positiv:** - **Negativ:** -
Nutzung von bzw. Zufriedenheit mit Geldausgabeautomaten	**Positiv:** Albesa (2007), Curran und Meuter (2005), Devlin und Yeung (2003) **Negativ:** -	**Positiv:** - **Negativ:** -

Tabelle C-5: Zusammenfassung der Faktoren, die Einfluss auf die Nutzung von Online- bzw. Mobile-Banking nehmen

Anzahl der genutzten Produkte ebenfalls positiven Einfluss nehmen. Im Kontext Mobile-Banking hat keine Studie diese Kovariaten einbezogen.

Der Einfluss der Konstrukte, welche sich auf andere Kanäle der Bank beziehen, sind ebenfalls eindeutig: *Vertrauen in bzw. räumliche Nähe zur Filiale* beeinflusst die Entscheidung Online-Banking zu nutzen positiv. *Nutzung von bzw. Zufriedenheit mit Geldausgabeautomaten* hat einen identischen Effekt. Negativen Einfluss nimmt hingegen *Nutzung von bzw. Zufriedenheit mit Filialtransaktionen.* Online-Banking Kunden sind somit über die Nutzung von Geldausgabeautomaten bereits mit Selbstbedienungstechnologien vertraut. Obwohl die Filiale von Ihnen weniger genutzt wird, wirkt Vertrauen in diese positiv auf die Entscheidung Online-Banking zu. Bedauerlicherweise fehlen Studien, welche diese Kriterien im Hinblick auf Mobile-Banking untersuchen.

Gegensätzlichen Einfluss zwischen Online- und Mobile-Banking nehmen die Variablen *Dauer der Geschäftsbeziehung, Höhe des Einkommens* sowie *Höhe der Kontosalden.* Während im Kontext Online-Banking erstere negativ und die beiden letzteren positiv korrelieren zeichnet sich für Mobile-Banking ein entgegengesetztes Bild ab: Hier nehmen erstere positiven und die beiden letzteren negativen Einfluss. Bemerkenswert ist, dass Liu, Abhishek und Li (2017) neben Mobile-Banking über das Smartphone auch Banking-Aktivitäten über das Tablet beobachten. Sie stellen fest, dass das Verhalten am Tablet in vielerlei Hinsicht ähnlich zu dem im Online-Banking ist. Unter anderem ist der Einfluss der soeben betrachteten Kovariaten bei Tablet-Nutzern identisch zu den Erkenntnissen der anderen Online-Banking Studien (negativ für die *Dauer*

der Geschäftsbeziehung sowie positiv für die *Höhe des Einkommens* und *Höhe der Kontosalden*).[38] Künftige Studien sollten diese drei Variablen in ihre Untersuchung aufnehmen und überprüfen, ob sich der Effekt zwischen Online- und Mobile-Banking tatsächlich als gegensätzlich bezeichnen lässt.
Online-Banking Kunden lassen sich demnach folgendermaßen charakterisieren:

> *In der Tendenz verfügen Online-Banking Kunden über ein höheres Einkommen und höhere Kontosalden, sind jünger sowie häufiger verheiratet und männlich, nutzen Geldausgabeautomaten und mehr Produkte der Bank, besitzen eine bessere Bildung und haben Kontakt zu anderen Online-Banking Kunden, generieren mehr Transaktionen mit sowie höhere Erträge für die Bank und weisen eine kürzere Geschäftsbeziehung zu dieser aus.*

Für Mobile-Banking Kunden ergibt sich folgende Charakterisierung:

> *In der Tendenz verfügen Mobile-Banking Kunden über ein geringeres Einkommen bei zugleich höheren Kontosalden, sind jünger sowie häufiger verheiratet und männlich, nutzen mehr Produkte der Bank, besitzen eine bessere Bildung und haben Kontakt zu anderen Mobile-Banking Kunden, generieren mehr Transaktionen mit und haben eine längere Geschäftsbeziehung zur Bank.*

Abschließend kann festgestellt werden, dass sich der Literaturumfang im Hinblick auf Online-Banking im Vergleich zu Mobile-Banking deutlich umfassender darstellt. Während ersteres bereits vielseitig erforscht zu sein scheint ergeben sich für Mobile-Banking noch einige Anknüpfungspunkte für künftige wissenschaftliche Arbeiten.

4.4.4 Skalierung der abhängigen Variablen

Einige Studien beschreiben Eigenschaften von OMB Kunden lediglich mit Hilfe deskriptiver Statistik und kontrollieren demnach nicht für Selbstselektion. Studien, die eine multivariate Regressionsanalyse durchgeführt haben, nutzen meistens eine dichotom skalierte Ergebnisvariable (Kunde nutzt OMB: Ja oder Nein). Es ist davon auszugehen, dass der Grad der Nutzung nicht bei allen Kunden gleich ist sondern kundenindividuell variiert. In diesem Fall vereinfacht eine dichotome Ergebnisvariable die Realität zu stark. Um bankseitig eine Strategie für Online- bzw. Mobile-Banking zu entwickeln sollte empirische Evidenz darüber bestehen, welche Funktionen von welchen Kundengruppen genutzt werden. Das Leistungsspektrum moderner Online- bzw. Mobile-Banking Anwendungen geht deutlich über klassische

[38] Vgl. Liu, Abhishek und Li (2017, S. 16).

Zahlungsverkehrsdienstleistungen hinaus und umfasst mittlerweile auch Möglichkeiten zur Vermögensallokation, Kreditaufnahme, Kommunikation mit dem Bankberater, Platzierung diverser Serviceanfragen uvm. Sowohl Lambrecht (2005, S. 153) als auch Campbell und Frei (2010, S. 13) untersuchen Veränderungen, die aus der Nutzung von Online-Banking resultieren und unterscheiden hierzu in aktive und passive Nutzer. Bei Ersterem gilt ein Kunde dann als aktiv, wenn er im Quartal mindestens eine Transaktion durchgeführt hat.[39] Inwiefern eine Transaktion je Quartal auf aktive Kanalnutzung schließen lässt, erscheint aus Sicht des Autors jedoch fraglich. Letztere bilden den Median der Online Transaktionen. Kunden mit mehr/weniger Transaktionen als der Median gelten anschließend als aktiv/passiv. Eine Unterscheidung anhand der genutzten Funktionen findet jedoch nicht statt.

Die Analyse von Tan und Teo (2000, S. 28) zeigt, dass die befragten Probanden die Nützlichkeit der diversen Online-Banking Funktionen unterschiedlich bewerten. Es muss berücksichtigt werden, dass dieses vielfältige Angebot nicht einheitlich sondern sehr heterogen angenommen wird. Daher wäre neben der Nutzungsintensität auch zu ergründen, inwiefern Kundeneigenschaften zur Nutzung unterschiedlicher Transaktionsarten (Serviceanfragen, Produktabschlüsse, finanzielle Transaktionen etc.) führen. Darüber hinaus sind zwingend Mobile-Banking Anwendungen mit einzubeziehen. Die bisherige Forschungslandschaft hat dieser Fragestellung nur ungenügend Rechnung getragen.

4.5 Fazit und Implikationen für künftige Studien

Die Literaturlandschaft, welche sich mit Online- bzw. Mobile-Banking auseinandersetzt, kann als umfassend bezeichnet werden. Die vorliegende Arbeit diskutiert einen Teilbereich dieser und hinterfragt, welche Eigenschaften Online- und Mobile-Banking Kunden in Deutschland besitzen. 26 empirische Studien leisten einen Beitrag zur Beantwortung dieser Fragestellung. Die Ergebnisse dieser wurden zusammengefasst und im Anschluss eine Charakterisierung jener Kunden abgeleitet.

Einige der Studien nutzen Modelle aus der Sozialpsychologie, welche in den meisten Fällen gute Ergebnisse erzielen und einen hohen Teil der Varianz erklären können. Außerdem wurde festgestellt, dass die meisten Untersuchungen Online- bzw. Mobile-Banking isoliert betrachten. Während einige Beiträge Online-Banking im Kontext mit anderen Kanälen der Bank untersuchen konnte keine einzige Untersuchung ermittelt werden welche Online- und Mobile-Banking im Kontext eines Multi-Kanal-Vertriebs betrachten. Hier ergibt sich ein relevantes Forschungsfeld für künftige Analysen, da diese Vertriebsstruktur typisch im deutschen Finanzdienstleistungssektor ist. Ferner wurde konstatiert, dass die Samplegenerierung bei Studien mit dem Fokus auf Online-Banking ausgewogen erscheint: Es finden sich sowohl Beiträge auf Basis von Fragebögen als auch auf Basis von Nutzungsdaten. Ebenfalls konnte eine Meta-Studie identifiziert werden. Im Kontext Mobile-Banking ergibt sich ein abweichendes Bild: Hier finden sich nur zwei Studien, welche Mobile-Banking

[39] Vgl. Lambrecht (2005, S. 153).

auf Basis tatsächlicher Nutzungsdaten untersuchen. Es zeigt sich somit eine weitere relevante Lücke, welche in Zukunft durch Analysen auf Basis von Nutzungsdaten geschlossen werden sollte. Nachfolgend wurde eruiert, dass die Beiträge, welche multivariate Verfahren instrumentalisieren, in der Regel eine dichotom skalierte Ergebnisvariable einsetzen. Dadurch wird lediglich zwischen Nutzern und Nicht-Nutzern unterschieden und die Realität stark vereinfacht. Online- und Mobile-Banking eröffnen mittlerweile diverse Funktionalitäten und es ist davon auszugehen, dass diese sehr heterogen genutzt werden. Künftige Untersuchungen sollten diese Tatsache berücksichtigen und detaillierter betrachten, welche Funktionen von welchen Kundengruppen genutzt werden.

Abschließend lässt sich festhalten, dass bereits diverse relevante Fragestellungen beantwortet werden konnten und eine breite Basis unterschiedlicher Beiträge vorhanden ist. Künftige Studien sollten Online- und Mobile-Banking stärker im Multi-Kanal-Umfeld betrachten und insbesondere im Hinblick auf Mobile-Banking tatsächliche Nutzungsdaten zur Generierung von Erkenntnissen operationalisieren. Außerdem wären weniger pauschalierende und vielmehr detailliertere Einblicke in die genutzten Funktionen hilfreich.

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5 Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

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Michel Becker

Gladenbach, den 29.01.2021

Submitted Papers

I. Becker, M., Stolper, O., Walter, A. (2021): The 24/7 anywhere branch: Mobile-banking improves financial decision-making – or does it? (Working Paper)

II. Becker, M., Stolper, O., Walter, A. (2021): The Impact of Mobile-Banking Adoption on Retail Banking (Technical Report)

III. Becker, M. (2019). Empirische Evidenz zu Eigenschaften von Online- bzw. Mobile-Banking Kunden in Deutschland. Zeitschrift für Bankrecht und Bankwirtschaft, 31(1), 42-58.