Does FinTech Affect Household Saving Behavior?
Findings from a Natural Field Experiment.

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Abstract

Using data from a natural field experiment with more than 65,000 customers of a large European bank, we measure the effect of a money management FinTech on household saving behavior. We find that individuals are more likely to start first-time saving and significantly increase their saving balances, after FinTech activation. However, we also find that customers with low financial literacy are less likely to activate the tool in the first place. Overall, our results suggest that emerging FinTechs indeed have the potential to affect household saving behavior.

JEL Classification: D14, D91, E21, O33

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Introduction

For more than five decades, household finance researchers document that households save less than predicted by normative theory, e.g., the life cycle consumption model by Modigliani and Brumberg 1954. Instead, people tend to overconsume and save too little in present periods (Thaler and Benartzi 2004; Laibson 1997; Ottaviani and Vandone 2011; Ashraf, Karlan, and Yin 2006)[1]. Insufficient household savings cause problems of economic relevance, e.g., deficient wealth at retirement (Lusardi and Mitchell 2007; Beshears et al. 2015) and over-indebtedness (Lusardi and Tufano 2009; Betti et al. 2007; Dynan and Kohn 2007). Therefore, researchers and regulators continuously address the discussion of ways to improve household finance management and to increase saving rates (Thaler and Benartzi 2004).

As one initial requirement to improve household finance, the need for increased transparency and reduced complexity was identified (Bernanke 2009; Lusardi 2008). In the past, however, households' efforts to enhance financial transparency resulted in high search and coordination costs. This made

[1]Saving rates as percentage of household disposable income have declined in the U.S., Europe and Germany since 2009 (OECD 2017).

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such activities economically unattractive (Campbell et al. 2011; Sirri and Tufano 1998; Kamenica, Mullainathan, and Thaler 2011).

Yet, recently surging financial technology services (FinTech)[2] promise to enhance consumer financial transparency and ease management of household finances (Chishti and Barberis 2016). One emerging class of FinTechs are money management tools, which allow the user to transparently manage her household consumption and income (Fowler, June 16, 2015). The tools' algorithms automatically analyze current account transactions and allocate amounts into spending or income categories, e.g., cost of living, residential expenses or salary. Thereby, the user can easily review monthly spending and income flows in a graphic interface. In addition, these tools offer budgetary planning and automated saving scheme features (Sharf, March 02, 2016).

Despite the growing dispersion in today's financial system, effects of these money management FinTechs on household finance have not been studied, yet. This article therefore studies *first*, who activates a money management FinTech and *second,* the effect of activation on households' saving behavior. *Third,* we assess who particularly benefits from usage and *fourth*¸ we test whether a change in day-to-day consumption behavior can be observed.

For our research, we cooperate with a large European retail bank and work with their proprietary money management FinTech. We analyze a rich dataset of 65,073 German customers obtained in a natural experiment (Harrison and List 2004) between August 2015 and March 2016. We observe financial balances prior and after money management FinTech activation for a group of users and a control group of non-users. Also, over 2 million current account transactions of customers who use the tool are available. To the best of our knowledge, this type of data is unique in research.

Previous studies already worked with data from FinTechs and could benefit from high data quality (Kuchler 2016; Gelman et al. 2014; Baugh, Ben-David, and Park 2014).[3] However, given their research design, difference-in-difference analyses about the effect of FinTech usage on household saving behavior were not feasible within these studies. With this article, we thus hope to complement previous analyses and add new insights to the research field of household saving behavior.

[2] The term FinTech refers to 'Financial Technology services', not to a start-up within the financial industry, in this article. Following Danker 2016, we stress that research so far lacks of a clear definition of 'FinTech'.

[3] Campbell 2006 mentions five quality criteria as ideal characteristics for household finance studies. Data should be representative for a larger part of the population and total household wealth should be observable. Sufficient granularity, a high level of accuracy and a structure as panel data should also be given. FinTech's digital nature allows for high accuracy, granularity and a panel structure. Also, individuals are representative in our dataset compared to e.g., the HFCS survey (Household Finance and Consumption Network 2016). Only, complete household wealth observation cannot be guaranteed with FinTech data.

We make several findings. *First*, customers who are male, younger, and have a more intense banking relationship, are more likely to activate the tool. We also find that customers with low saving balances prior to the experiment are more likely to activate the FinTech. *Second*, the average customer's monthly savings balance significantly increases after tool activation by 268 EUR. Average monthly current account balance significantly increases by 176 EUR and total deposits held at the bank increase on average by 409 EUR in the post-activation period. The latter equals an increase of 4.2% compared to pre-experiment deposits. *Third*, we identify that customers without any observable saving activity prior to the treatment are more likely to start first time saving, after tool activation and can thus benefit from the FinTech. *Fourth*, we find that the increase in savings balance is driven by amplified spending on saving plans which can easily be setup within the money management FinTech and that these contributions persist during our observation period. The increase in the current account balance is largely driven by customers who transfer salary inflows to the bank, after tool activation. Yet, we also find evidence that active tool usage for most customers declines already in the first month post activation. Together with the fact that changes in consumption splits are economically hardly relevant, this implies that the tool's feature to set automatic default saving plans is of high relevance in changing the saving behavior. This is in line with previous work on the importance of defaults and mental accounting for saving success (Thaler and Benartzi 2004; Choi et al. 2001; Shefrin and Thaler 2004; Thaler 1985).

Overall, our findings suggest that FinTechs such as money management tools indeed affect household financials and can spur savings. While less wealthy customers are more likely to activate the tool, we also find that the tool is less likely to be activated by financially less educated customers in the first place. A comparable selection behavior was also found by studies for other areas of financial support.[4] Our results contribute towards the research field of household saving and lifecycle consumption studies. Also, we hope to add new perspectives to regulators' and practitioners' discussions about FinTechs' economic potential and high financial valuations of FinTech services.

The rest of this article is structured as followed. Section 1 explains the field experiment and the money management tool. Section 2 describes the data and provides descriptive statistics on users and non-users. Section 3 analyzes, who most likely activates the tool. In section 4, we assess effects of tool activation on customers' financials, incl. saving balances. Section 5 focuses on heterogeneity between subgroups. Section 6 runs within-subject event studies on income and spending behavior for customers who activated the tool. Section 7 concludes by summarizing our findings and providing questions for future research.

[4] For example, Bhattacharya et al. 2012 find financial advice is sought less often by customers who might need it the most.

1. Field experiment

Within this chapter, we provide an overview on the cooperating bank, the money management FinTech and the timeline of our natural experiment.

We cooperate with a large European financial institution with more than 50,000 employees and over five million global customers. At the end of 2014, the bank decided to launch a new, free of charge feature within its online banking environment – a money management tool. This new class of FinTechs is already widely established in the US, by both third parties, e.g., “mint.com” and as bank proprietary solutions (Reuters 2015; Fischer and Wagner 2015).

The observed money management tool’s algorithm automatically allocates customers’ current account transactions into monthly inflow and outflow categories. Categories are defined based on classifications typically used by governmental statistic organizations, e.g., the German National Bureau of Statistics (Statistisches Bundesamt 2016)[5]. To allocate a transaction into a category, the algorithm uses several thousand rules which analyze multiple transaction data elements. In particular, the tool uses ISO purpose codes (ISO 2014), creditor IDs which are part of the European SEPA Card Clearing Framework (Metzger 31/12/2014), textual analysis and internal codes, e.g., to identify cash withdrawals. If a transaction cannot clearly be allocated to one category, it is labeled as uncategorized and is left for manual allocation by the user.[6]

Based on these categorizations, the user can analyze recent spending behavior in a graphic interface. The main page includes graphical month-by-month review of inflows and outflows, as well as share and absolute value per spending category, e.g., cost of living, or spending on saving and investment activities. Also, the customer can review her automatically pre-filled or manually entered monthly budgets per category. She also can analyze the completion status of her self-implemented saving targets. The cockpit is completed by a review of last transactions and an overview on share of non-categorized transactions. Customers can access the tool online or via the bank’s mobile app. An anonymized example of the money management FinTech can be found in Appendix A.

Our natural field experiment takes place in Germany, one of the bank’s major markets, between September 1st 2015 and February 29th 2016. Our total sample of 65,073 customers was drawn from

[5] Allocation of expenses into categories on a monthly basis is a common approach used by households and based on mental accounting (Thaler 1985).

[6] In our observation period, 444,410 transactions remained uncategorized which are 15.3% of all transactions. Total volume of all transactions is 889 EURmn during the observed period, of which 447EURmn (50.3%) are inflows and 442EURmn outflows (49.7%). Virtually all non-categorized transactions are outflows, only 5 transactions with a volume of 2,210 EUR are inflows. Total volume of non-categorized transactions is 179 EURmn. The algorithm’s beta error follows a rather conservative approach. If a transaction is allocated into a category, it is therefore very sure that the allocation is correct.

the bank's total population of several million customers with an online banking current account in a stratified randomization scheme[7]. All customers received the same invitation to activate the money management FinTech within their online banking environment via a pop-up note at online banking login. We observe individual customers and are able to track their enrollment decision, monthly financial balances and if they enroll into the tool, also their individual transactions prior and post tool activation. During this period 15,077 customers activated their money management tool[8]. 49,996 customers in our sample who did not activate the tool are used as control group.

2. Data and Descriptive Statistics

Within this chapter, we first describe the type of data collected. We subsequently provide descriptive statistics on treatment and control group and derive first indicative insights from univariate analyses.

2.1. Data collected

Our first part of the dataset includes demographic and bank relationship data for our entire sample population of 65,073 customers. ***Table 1*** provides an overview on the data collected. Our data include gender, age, marital status, employment status, first digit of the ZIP code, length of customer relationship, number of branch visits over the last 12 months, information on product types owned at this bank, the bank's internal credit risk score and the date of FinTech activation (if applicable).

The second part of our data are customers' financial balances and include current account, portfolio, debit, i.e. lending, and credit, i.e. borrowing, balances at the end of each month from August 2015 to March 2016. As customers' total debit (credit) balances include both – pure savings (credit) products and any positive (negative) current account balance – pure savings and pure credit product balances at the end of each month are reported, too. Furthermore, we observe total monthly wealth held with the bank, which is the difference of monthly debit less credit balance.

The third part of data includes individual transaction data, for customers who activated the money management tool, from November 1st 2015 to March 31st 2016. We use this data in the within subject event studies. This data includes date and amount of transaction, allocated category and a dummy variable, whether a transaction was re-categorized manually.

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[7] We stratify for tool users and non-users and then randomly draw customers. From our total sample of 65,073 customers we previously excluded 3,370 customers (2,220 in treatment and 1,150 in control group), who were with the bank less than 150 days by August 2015 to remove effects from new customers. Also, we removed 64 customers (3 in treatment and 61 in control group) with incomplete financial balances and 217 customers who left the bank before the end of our observation period (51 in treatment, 166 in control group) to allow for a balanced panel structure. Given the short observation period, the low number of customers leaving the bank and the overall sample size, we prefer the balanced panel over a research design adjusted for potential survivorship bias (Brown et al. 1992).

[8] 1,836 customers enrolled in September 2015 and 1,667 in October. 1,561 joined in November and 3,186 in December. 3,376 registered in January 2016 and 3,451 in February 2016.

Table 1: Description of data structure

Type of data	Data variable	Periods and frequency available	Number of observations
Customer demographics & bank relationship data	Gender	Time-invariant	59,126
	Age	Time-invariant	59,126
	Marital status	Time-invariant	65,073
	Employment status	Time-invariant	65,073
	ZIP code region	Time-invariant	65,073
	Duration of bank relationship	Time-invariant	64,938
	Number of branch visits last 12 months	Time-invariant	65,073
	Dummy saving plan product(s) owned	Time-invariant	65,073
	Dummy saving product product(s) owned	Time-invariant	65,073
	Dummy retirement product(s) owned	Time-invariant	65,073
	Dummy consumer credit product(s) owned	Time-invariant	65,073
	Dummy credit card product(s) owned	Time-invariant	65,073
	Dummy mortgage product(s) owned	Time-invariant	65,073
	Credit risk score	Time-invariant	65,073
	Day of money management tool activation (users only)	Time-invariant	15,077
Financial balances	Current account balance	Monthly, Aug'15 - Mar'16	520,584
	Debit balance	Monthly, Aug'15 - Mar'16	520,584
	Pure savings balance (debit excl. positive current account)	Monthly, Aug'15 - Mar'16	520,584
	Credit balance	Monthly, Aug'15 - Mar'16	520,584
	Pure credit balance (credit excl. negative current account)	Monthly, Aug'15 - Mar'16	520,584
	Wealth held with the bank (debit less credit balance)	Monthly, Aug'15 - Mar'16	520,584
	Portfolio balance (for customers who own a portfolio)	Monthly, Aug'15 - Mar'16	520,584
Transaction data (for tool users, only)	Day and time of transaction	Instantly, Oct'15- Mar'16	2,889,227
	Transaction amount	Instantly, Oct'15- Mar'16	2,889,227
	Assigned main category	Instantly, Oct'15- Mar'16	2,889,227
	Assigned sub-category	Instantly, Oct'15- Mar'16	2,889,227
	Information whether transaction was manually relocated	Instantly, Oct'15- Mar'16	2,889,227

Table 1 summarizes data collected in the natural field experiment. Type of data and data variable are reported in the first and second column. In the third column, we describe available periods and frequency. Column four shows the total number of data points per variable. 5,947 data cells are empty for gender and age, as these are accounts, jointly owned by at least two people. 135 data points on length of customer relationship were missing in the sample.

2.2 Descriptive statistics

Table 2 reports summary statistics of our natural field experiment. We distinguish between 15,077 customers who activated the tool between September 1st 2015 and February 29th 2016, the 'treatment group', and 49,996 customers who did not activate the tool, the 'control group'. ***Table 2*** also provides P-values of univariate t-tests on equality of means between the treatment and control group. We run a skewness and kurtosis test for normality (D'agostino, Belanger, and D'agostino, JR 1990) and find that financial balances are not normally distributed. Therefore, we additionally report P-values of a nonparametric Mann-Whitney statistic (Mann and Whitney 1947). Results and descriptive statistics are grouped into demographic, banking relationship and financial variables.

As reported in ***Table 2***, we find that 59.0% of customers who activated the money management tool are men, while only 54.4% of customers in the control group are male. With a mean age of 38.8 years, customers in the treatment group are significantly younger than the control group with a mean age of 43.0. In particular, we find that the majority of tool users is between 16 and 40 years, while the majority of customers in the control group are 26-50 years. Marital status is also significantly different between

Table 2: Demographic, banking relationship and financial characteristics of customers who activate and do not activate the money management tool

		Activate the tool			Do not activate the tool			t-test	Mann-Whitney test	Difference
Data variable	Measurement units	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	(A)-(B)
		Client demographics								
Gender	Dummy=1 if male	59.0%	1	13,670	54.4%	1	45,456	.00	.00	4.6%
Age	Years	38.8	36.0	13,670	45.0	43.0	45,456	.00	.00	-6.23
Age 0-15	Dummy=1 if Age 0-15	0.0%	0	15,077	0.0%	0	49,996	.72	.72	
Age 16-25	Dummy=1 if Age 16-25	14.1%	0	15,077	6.7%	0	49,996	.00	.00	7.4%
Age 26-40	Dummy=1 if Age 26-40	42.4%	0	15,077	33.1%	0	49,996	.00	.00	9.4%
Age 41-50	Dummy=1 if Age 41-50	17.6%	0	15,077	20.9%	0	49,996	.00	.00	-3.4%
Age 51-65	Dummy=1 if Age 51-65	11.7%	0	15,077	19.5%	0	49,996	.00	.00	-7.9%
Age 65plus	Dummy=1 if Age 65plus	4.9%	0	15,077	10.7%	0	49,996	.00	.00	-5.9%
Joint account	Dummy=1 if Joint account	9.3%	0	15,077	9.1%	0	49,996	.34	.34	
Single	Dummy=1 if single	50.1%	1	15,077	41.1%	0	49,996	.00	.00	9.0%
Civil union	Dummy=1 if civil union	0.2%	0	15,077	0.1%	0	49,996	.06	.06	0.1%
Married	Dummy=1 if married	30.7%	0	15,077	36.9%	0	49,996	.00	.00	-6.2%
Separated	Dummy=1 if separated	1.7%	0	15,077	1.7%	0	49,996	.96	.96	
Divorced	Dummy=1 if divorced	5.8%	0	15,077	7.0%	0	49,996	.00	.00	-1.2%
Widowed	Dummy=1 if widowed	1.8%	0	15,077	3.5%	0	49,996	.00	.00	-1.7%
No marriage reported	Dummy=1 if nothing reported	9.7%	0	15,077	9.7%	0	49,996	.02	.02	0.0%
Self-employed	Dummy=1 if self-employed	0.8%	0	15,077	0.9%	0	49,996	.47	.47	
Employees	Dummy=1 if employee	38.9%	0	15,077	36.6%	0	49,996	.00	.00	2.2%
Public employees	Dummy=1 if public employee	2.1%	0	15,077	2.1%	0	49,996	.59	.59	
Industrial worker	Dummy=1 if industrial worker	9.2%	0	15,077	9.3%	0	49,996	.68	.68	
Students	Dummy=1 if student	19.8%	0	15,077	14.2%	0	49,996	.00	.00	5.6%
Housewife	Dummy=1 if housewife	2.2%	0	15,077	2.7%	0	49,996	.00	.00	-0.5%
Retiree	Dummy=1 if retiree	3.4%	0	15,077	7.1%	0	49,996	.00	.00	-3.7%
Unemployed	Dummy=1 if unemployed	3.9%	0	15,077	3.9%	0	49,996	.90	.90	
No job reported	Dummy=1 if nothing reported	19.8%	0	15,077	23.2%	0	49,996	.00	.00	-3.4%
Zip code region 0 (East)	Dummy=1 if zip code region 0	7.7%	0	15,077	8.1%	0	49,996	.11	.11	
Zip code region 1 (East)	Dummy=1 if zip code region 1	13.9%	0	15,077	16.4%	0	49,996	.00	.00	-2.5%
Zip code region 2 (North)	Dummy=1 if zip code region 2	12.0%	0	15,077	12.3%	0	49,996	.28	.28	
Zip code region 3 (Central)	Dummy=1 if zip code region 3	7.9%	0	15,077	7.5%	0	49,996	.12	.12	
Zip code region 4 (West)	Dummy=1 if zip code region 4	17.3%	0	15,077	17.3%	0	49,996	.96	.96	
Zip code region 5 (West)	Dummy=1 if zip code region 5	10.9%	0	15,077	10.8%	0	49,996	.24	.24	
Zip code region 6 (South-West)	Dummy=1 if zip code region 6	10.8%	0	15,077	9.4%	0	49,996	.00	.00	1.4%
Zip code region 7 (South-West)	Dummy=1 if zip code region 7	8.6%	0	15,077	6.9%	0	49,996	.00	.00	1.7%
Zip code region 8 (South)	Dummy=1 if zip code region 8	7.2%	0	15,077	7.5%	0	49,996	.21	.21	
Zip code region 9 (South-East)	Dummy=1 if zip code region 9	3.8%	0	15,077	4.0%	0	49,996	.28	.28	

Table 2 continued

Data variable	Measurement units	Activate the tool Mean (A)	Median	N	Do not activate the tool Mean (B)	Median	N	t-test P-Value	Mann-Whitney test P-Value	Difference (A)-(B)
Bank relationship										
Length of banking relationship	Years	12.3	9.5	15,064	15.5	12.9	49,874	.00	.00	-3.17
Intensity of banking relationship	# of branch visits p.a.	1.0	0.0	15,077	0.7	0.0	49,996	.00	.00	0.34
Saving plan	Dummy=1 if 'Saving plan' owned	41.1%	0	15,077	36.6%	0	49,996	.00	.00	4.5%
Saving product	Dummy=1 if 'Saving product' owned	9.0%	0	15,077	11.0%	0	49,996	.00	.00	-2.0%
Retirement product	Dummy=1 if 'Retirement product' owned	15.6%	0	15,077	13.7%	0	49,996	.00	.00	1.9%
Credit card	Dummy=1 if 'Credit card' owned	24.7%	0	15,077	23.1%	0	49,996	.00	.00	1.6%
Consumer credit	Dummy=1 if 'Consumer credit' owned	14.2%	0	15,077	10.5%	0	49,996	.00	.00	3.7%
Mortgage	Dummy=1 if 'Mortgage' owned	4.2%	0	15,077	4.3%	0	49,996	.86	.86	
Credit default risk	Bank credit score (0=low - 1=high)	0.009	0.003	15,077	0.007	0.002	49,996	.00	.00	0.002
Financials										
Cash at t=0 (August 2015)	€	5.591	1.116	15,077	6,847	1,452	49,996	.00	.00	-1255.93
Low cash	Dummy=1 if cash in t=0 is lowest decile	11.0%	0	15,077	9.7%	0	49,996	.00	.00	1.4%
High cash	Dummy=1 if cash in t=0 is highest decile	8.4%	0	15,077	10.5%	0	49,996	.00	.00	-2.0%
Share of portfolio owners	Dummy=1 if portfolio is owned	10.3%	0	15,077	11.3%	0	49,996	.00	.00	-1.0%
Portfolio value at t=0 (August 2015)	€, if portfolio is owned	66.189	7.939	1,554	92,756	15,318	5,664	.00	.00	-26567.27
Debit value at t=0 (August 2015)	€	9.648	1.477	15,077	12,103	1,950	49,996	.00	.00	-2454.44
Low debit	Dummy=1 if debit in t=0 is lowest decile	11.7%	0	15,077	9.5%	0	49,996	.00	.00	2.2%
High Debit	Dummy=1 if debit in t=0 is highest decile	8.2%	0	15,077	10.5%	0	49,996	.00	.00	-2.3%
Credit value at t=0 (August 2015)	€	7.106	0	15,077	5,967	0	49,996	.00	.00	1139.09
Low credit	Dummy=1 if credit in t=0 is lowest decile	74.7%	1	15,077	78.1%	1	49,996	.00	.00	-3.3%
High credit	Dummy=1 if credit in t=0 is highest decile	11.9%	0	15,077	9.4%	0	49,996	.00	.00	2.5%

Table 2 reports summary statistics on customer demographics, bank relationship variables and financial balances. The columns ‘Activate the tool’ and ‘Do not activate the tool’ show means, median values and quantity of observations for each group. Next, we report p-values of a univariate t-test on difference of means and p-values of a univariate Mann-Whitney test, which does not require a normally distributed sample. Finally to facilitate ease of reading, if significant differences were found, the last columns shows the mean difference between treatment group mean (A) and control group mean (B). Customer demographics include information on the proportion of male customers (*Gender*), customers’ age (*Age),* and respective distribution between age groups (*Age 0-15, Age 16-25, Age 26-40, Age, 41-50, Age 51-65, Age 65 plus*). *Joint account* identifies share of accounts in each group that are owned by more than one person. Distribution between the groups of marital status is reported in the variables *Single, Civil Union, Married, Separated, Divorced, Widowed* based upon customers’ reported status. If the status was not provided, *No marriage reported* was set to 1. *Employee, house wife, retiree, unemployed, public employee,* and *industrial employee* report customers’ employment status. *Self-employed* includes customers who work as executives or owner of a firm, while *student* includes (high school) pupils, regular students and pupils of technical apprenticeships. *No job reported* identifies customers who did not provide a job information. We use customers’ registration address’ first zip code number to identify their region of living (*Zip code region 0-9).*We report the number of years, a customer was with the bank (*length of relationship)* and the *intensity of relationship*, measured as the number of branch visits within the last 12 months. We report whether a customer owns at least one product from a specific product category (*Saving plan, Saving product, Retirement product, Credit card, Consumer credit, Mortgage, Portfolio owned).* The bank’s internal risk score (*credit default risk)* ranges from 0 (low) to 1 (high). We compare customers’ initial balances on August 31st 2015 (t=0) for current account (C*ash)*, deposits (Debit) and overall borrowings (Credit). Portfolio values (*portfolio)* are reported, if a portfolio was owned. For current account, deposits and credits we take the first and the last decile at t=0 and report the results, too (*Low cash, High cash, Low debit, High Debit, Low credit, High credit)*.

the two groups[9]. Also, we find that significantly less retirees are in the treatment group (3.4%), compared to the control group (7.1%).

Within our group of activators, we have a significantly higher share of customers from South-West Germany. 10.8% (8.6%) of customers in the treatment group are from zip code area 6 (7) compared to 9.4% (6.9%) in the control group. On the other hand, customers from East Germany (zip code 1) register significantly less, with 13.9% in the treatment group compared to 16.4% in the control group. As customers from East Germany are on average financially less literate (Bucher-Koenen and Lusardi 2011; Fuchs-Schundeln and Schundeln 2005), this could already indicate that customers who are financially less educated activate the tool less often.

Considering customers' banking relationship, we find that those who activate the tool have a significantly shorter banking relationship length than those who do not, with on average 12.3 years compared to 15.5 years[10]. Yet, customers in the treatment group have significantly more branch visits within the last 12 months (on average 1.0) compared to the control group (0.7). All of the results above are later confirmed in a multivariate probit tests.

We also consider debit balances at t=0 and find that average debit balance of 9,648 EUR in the treatment group is significantly below the average of 12,103 EUR in the control group. This difference is significant also in the non-parametric Mann-Whitney test. Additionally, we find that significantly more customers from the lowest decile of debit balances, activate the tool (11.7% compared to 9.5% in the control group).[11] This finding is later confirmed in a multivariate probit analysis. [12]

Finally, we find that customers who activate the tool, less often own an investment portfolio (10.3% vs. 11.3% in the control group). If they own a portfolio, their average (median) balance is significantly lower 66,189 EUR (7,939 EUR) compared to 92,756 EUR (15,318 EUR). We confirm in a multivariate test that customers with high portfolio balances register significantly less. So, financially very experienced customers might not see the need to activate the money management tool.

Based on descriptive statistics, we find indicative evidence that the money management FinTech is more often activated by young, male customers, who are financially literate and are more engaged in managing their personal finance at the bank. Yet, they also have significantly lower debit balances and

[9] We find that significantly more singles (50% in treatment group vs. 41% in the control group) and customers in civil unions use the tool. On the other hand, less married, divorced and widowed customers register during our field experiment. However, these results do not remain significant in a multivariate probit test.
[10] Part of this difference is driven by younger customers in the group of activators. Still, the result is robust in a multivariate analysis.
[11] Bottom decile of debit balances are below 9.27€ in August 2015, top decile with more than 23,681.52€.
[12] While current account balances differ significantly in univariate tests (means of 5,591 EUR in the treatment and 6,847 EUR in the control group in August 2015 (t=0)), differences are not robust in later multivariate robust probit analyses. The same holds for credit balances at t=0.

lower current account balances. Young, German men were found to be particularly vulnerable to over-indebtedness (Finke 2014) and German households with low liquidity have difficulties to start saving (Späth and Schmid 2016). These first results thus indicate that a group of customers who typically is in need for better financial management might more often activate the tool. However, we also find evidence that groups with typically lower financial knowledge appear less interested in activating the tool.

3. Who Activates the Money Management Tool?

We now formally assess who is most likely to activate the money management tool to test univariate results for robustness. ***Table 3*** reports the results of four robust probit tests with Huber-White heteroscedasticity consistent standard errors (White 1980; Huber 1967). The dependent variable 'registration for money management tool' is set to one, if a customer decided to activate the tool. The variable is set to zero, if the customer did not activate the tool before February 29th 2016. We complete the regression of demographic control variables (1), with banking relationship (2) and financial variables (3) & (4).

We can draw the following conclusions. Although the majority of our population is male, being male significantly increases tool activation likelihood. If customers are young, we find that they are also more likely to register, while very young customers are less likely to participate. This is confirmed by the fact that students and retirees are both less likely to activate the tool compared to employees. However, we find that industrial workers show a significantly lower likelihood to register for the tool. Also, we find that regional differences remain. Customers from South-West regions more likely use the tool, than customers from East Germany.

Considering banking relationship, customers are more likely to register, if they have an intense banking relationship in terms of branch visits over the last twelve months. Customers who hold a portfolio at the bank, have a savings plan, a consumer credit, or a credit card are also significantly more likely to activate the household planning tool.

Finally, we find that lower portfolio balances and being in the lowest decile of savers/debit balances at t=0 (August 2015) significantly increases the likelihood to activate the money management tool. This result has a beneficial economic relevance since it indicates that customers with low wealth levels today, are more attracted by the tool and thereby could benefit from any potentially positive effect of tool usage. On the other hand, owning many different product categories, frequently visiting the branch, living in South-West Germany and not being unemployed nor an industrial worker which all leads to an increased activation likelihood, indicates that some basic financial literacy typically exists before activation (Lusardi and Mitchell 2007; Mincer 1991; Fuchs-Schundeln and Schundeln 2005). So, customers who need the tool more likely, actually *only* activate it, if at least some basic financial knowledge is existent. Comparable behavior is observed in other areas of personal finance. For example Bhattacharya et al. 2012 find customers with low financial sophistication less likely seek advice, although they benefit extraordinarily if they do so.

Table 3: Result probit analyses tool activation likelihood

	Registration for money management tool			
Dependent variable	(1)	(2)	(3)	(4)
Dummy male	0.163***	0.167***	0.167***	0.167***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Age	-0.056***	-0.055***	-0.055***	-0.055***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Age²	0.000***	0.000***	0.000***	0.000***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy civil union	0.354**	0.326**	0.325**	0.323**
	(0.01)	*(0.02)*	*(0.02)*	*(0.02)*
Dummy married	0.076***	0.069***	0.068***	0.067***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy divorced	0.177***	0.136***	0.134***	0.134***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy separated	0.181***	0.156***	0.155***	0.154***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy widowed	0.152***	0.062	0.063	0.061
	(0.00)	*(0.16)*	*(0.15)*	*(0.17)*
Dummy no marriage reported	-0.054	0.014	0.012	0.020
	(0.53)	*(0.87)*	*(0.89)*	*(0.82)*
Dummy self-employed	0.013	0.017	0.030	0.021
	(0.83)	*(0.78)*	*(0.63)*	*(0.74)*
Dummy public employee	0.014	-0.006	-0.007	-0.003
	(0.73)	*(0.88)*	*(0.87)*	*(0.94)*
Dummy industrial employee	-0.082***	-0.090***	-0.085***	-0.088***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy student	-0.223***	-0.137***	-0.135***	-0.134***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy housewife	-0.027	0.039	0.041	0.041
	(0.47)	*(0.31)*	*(0.29)*	*(0.28)*
Dummy retiree	-0.050	-0.075**	-0.077**	-0.753**
	(0.15)	*(0.03)*	*(0.03)*	*(0.03)*
Dummy unemployed	-0.085***	-0.007	-0.005	-0.006
	(0.00)	*(0.82)*	*(0.88)*	*(0.83)*
Dummy no job reported	-0.161***	-0.111***	-0.108***	-0.112***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Zip code region 0 (East)	-0.033	-0.015	-0.015	-0.014
	(0.18)	*(0.54)*	*(0.53)*	*(0.56)*
Zip code region 1 (East)	-0.099***	-0.081***	-0.080***	-0.080***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Zip code region 2 (North)	-0.031	-0.027	-0.027	-0.027
	(0.14)	*(0.19)*	*(0.20)*	*(0.20)*
Zip code region 4 (West)	-0.004	-0.005	-0.005	-0.005
	(0.81)	*(0.78)*	*(0.79)*	*(0.79)*
Zip code region 6 (South-West)	0.067***	0.069***	0.700***	0.071***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Zip code region 7 (South-West)	0.077***	0.073***	0.073***	0.073***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Zip code region 8 (South)	-0.059**	-0.060**	-0.060***	-0.059**
	(0.02)	*(0.02)*	*(0.00)*	*(0.02)*

Table 3 continued

	Registration for money management tool			
Dependent variable	(1)	(2)	(3)	(4)
Length of banking relationship		-0.008***	-0.008***	-0.008***
		(0.00)	*(0.00)*	*(0.00)*
Intensity of banking relationship		0.059***	0.063***	0.059***
		(0.00)	*(0.00)*	*(0.00)*
Portfolio		0.028	0.048**	0.036**
		(0.18)	*(0.03)*	*(0.09)*
Savings Plan		0.130***	0.126***	0.134***
		(0.00)	*(0.00)*	*(0.00)*
Consumer credit		0.094***	0.089***	0.075**
		(0.00)	*(0.00)*	*(0.01)*
Credit card		0.064***	0.063***	0.065***
		(0.00)	*(0.00)*	*(0.00)*
Retirement Product		0.027	0.025	0.027
		(0.12)	*(0.16)*	*(0.13)*
Savings Product		-0.013	-0.009	-0.001
		(0.55)	*(0.69)*	*(0.97)*
Mortgage		0.025	0.021	0.018
		(0.51)	*(0.61)*	*(0.69)*
Credit default risk		1.1***	1.1***	0.8***
		(0.00)	*(0.00)*	*(0.00)*
Cash at t=0 (August 2015)			-2.46E-08	
			(0.93)	
High cash at t=0				0.0
				(0.95)
Low cash at t=0				0.0
				(0.43)
Debit Balance at t=0 (August 2015)			-7.72E-09	
			(0.97)	
High Debit at t=0				0.0
				(0.37)
Low debit at t=0				0.1***
				(0.00)
Credit Balance at t=0 (August 2015)			3.04E-08	
			(0.84)	
High credit at t=0				0.0
				(0.95)
Low credit at t=0				0.0
				(0.53)
Portfolio value at t=0 (August 2015)			-3.78E-07***	
			(0.00)	
Constant	0.870***	0.708***	0.713***	0.721***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Observations	59,126	58,996	58,996	58,996
Pseudo-R²	0.0415	0.0522	0.0526	0.0527

Table 3 reports probit estimates of the money management tool activation in our natural field experiment. The dependent variable 'Registration for money management tool' is set to one, if a customer activated the money management tool during the observation period September 1st 2015 – February 29th2016. To estimate the probit model, we use the following independent variables: a dummy that is set to one if the customer is a man (*male),* customer age (*Age)* and squared age (*Age²*), dummies that are set to one depending on customer's relationship status (*civil union, married, divorced, separated, widowed, no marriage reported);* dummies which equal one, contingent on customer's reported job (*self-employed, public employee, student, housewife, retiree, unemployed, no job reported*) dummies which equal one, dependent on customer's region of living (*zip code region 0, zip code region 1, zip code region 2,zip code region 4, zip code region 6, zip code region 7 and zip code region 8)*[13], the number of years a customer has been with the bank (*Length of banking relationship*), the number of branch visits within the last 12 months (*Intensity of banking relationship*), dummies that are set to one, if a specific banking product is owned (*Portfolio, Savings Plan, Consumer credit, Credit card, Retirement Product, Savings Product, Mortgage*), bank's internal default risk calculation with 0 being low and 1 being the maximum (*Credit default risk)*, customer's current account balance in August 2015 (*Cash at t=0),* a dummy that is set to one, if the current account balance in August 2015 was in the lowest/highest decile (*High cash at t=0/Low cash at t=0*), customer's debit balance in August 2015 (*Debit Value at t=0),* a dummy that is set to one, if the debit balance in August 2015 was in the lowest/highest decile (*High Debit at t=0/Low debit at t=0*), customer's credit balance in August 2015 (*Credit Value at t=0),* a dummy that is set to one, if the credit balance in August 2015 was in the lowest/highest decile (*High credit at t=0/Low credit at t=0*) and customer's portfolio balance in August 2015 (*Portfolio value at t=0*).P-values are reported below coefficients in brackets. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level. Heteroscedasticity robust standard errors are used. Pseudo R² values and observations in the regression are reported. Differing number of observations is driven by missing data for banking relationship, gender and age (see Table 2).

[13] We do not include zip code regions 3, 5 and 9 in Table 2 as these regions in Central, Western and Eastern Germany were not significant in the univariate tests and jointly serve as a reference group.

To summarize, we understand well, which customers choose to activate the money management FinTech. Customers who are young men, have low savings and portfolio balances and thus might have lower financial experience (Calvet, Campbell, and Sodini 2007, 2009) are more likely to accept the tool activation invitation and could thus benefit from better household finance management. However, while customers with lower financial experience and lower wealth levels are attracted, some basic (financial) education seems to be required to activate the tool.[14]

4. Does the Tool Affect the Average User?

Within this chapter, we first describe how the balanced panel structure was created and then report results of the difference-in-difference panel regression analyses.

Given our research design as a natural experiment, we assess the effect of money management tool activation by applying a difference-in-difference methodology. This requires comparing treatment group customers' current account, debit, pure savings, and total wealth balances (from now on '*financials*') in the pre-activation period to respective balances in the post-activation period.

Since customers who decide to activate the money management tool might behave systematically different from customers who do not activate the tool, we use coarsened-exact matching (CEM) (Iacus, King, and Porro 2012) in combination with subsequent nearest neighbor Mahalanobis propensity score matching (Leuven and Sianesi 2003; Rosenbaum and Rubin 1983). Thereby, we aim to reduce observable imbalances in covariates between treatment and control group. As demonstrated by, Ho et al. 2007, this reduces statistical bias and allows to derive better causal inferences. [15]

CEM temporarily coarsens each variable into substantively meaningful groups. The CEM algorithm thereby minimizes the multivariate imbalance of covariates for treatment and control group. The exact match occurs based on these groups. With our data, we build groups based on gender, age, marital status, reported job type, length of banking relationship, number of annual branch visits, as well as current account, debit and credit balance at t=0 (August 2015). 1,832 customers in the treatment group remain unmatched as there was no sufficiently comparable control observation and are thus dropped.[16] We are left with 13,245 customers in our treatment group.

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[14] An alternative hypothesis for observed results is that digital nature of the FinTech attracts young, male customers. Yet, this could not explain the observed differences between activators and non-activators in region and job profiles. Another alternative hypotheses is that customers who activate the tool are more likely to have the majority of their financials at our cooperating bank. However, in this case, we would not expect that customers with lower saving balances and shorter banking relationship more likely activate the tool.

[15] For recent applications of these matching techniques consider, e.g., Li, Xia, and Lin 2016; DUYGAN-BUMP et al. 2013 and Faulkender and Yang 2010; Chemmanur, Loutskina, and Tian 2014.

[16] We report descriptive statistics on dropped customers from the treatment group in Appendix B.

For the subsequent nearest neighbor Mahalanobis propensity score matching without replacement, we take the probit model 4 in ***Table 3*** as it has the highest pseudo R^2 value. We match 13,245 customers who activated the tool with 13,245 customers from the control group. To build on the benefits of the already occurred CEM matching, the nearest neighbor is selected based on propensity scores within each "strata" (Iacus, King, and Porro 2012, 5), i.e. within each group of users and non-users that are comparable along observable criteria. This ensures that the propensity score matching is only matching customers who are indeed comparable based on observable characteristics. As we have a lot of control variables, we are thus confident to get as close as possible to a full randomization. Univariate mean comparison t-tests find no significant difference along all observed variables between treatment and control group. We report the comparison of matched treatment and control group in Appendix C.[17] Our panel consists of 13,245 users and non-users each. For all these customers we have 8 months (August 2015-March 2016) of their *financials* month-end balances, generating a total of 210,920 observations per *financial*.

Next, we build on the methodology used by, e.g., Bertrand and Mullainathan 2003 in a comparable research design, and run multivariate, cluster robust DiD regression analyses to assess whether money management tool activation affects household *financials*. Regressions have the following form.

Formula 1: Cluster robust DiD OLS regression of monthly financial balances

$$Y_{i,j} = \alpha + \beta * T_i + y * t_j + \Omega * T_i t_j + \Phi * X_i + e_{i,j} \tag{1}$$

$Y_{i,j}$ is the dependent *financial* variable of individual i in month j. T_i is a treatment dummy which is set to 1 if the customer has activated the money management tool. t_j is a dummy variable to identify pre- and post-treatment periods (monthly usage).[18] The interaction term variable '$T_i t_j$' for each month j is the product of T_i and t_j. It equals one for months in which customers in the treatment group had the money management tool activated and thus is our variable of interest. X_i indicates demographic, banking relationship and financial control variables as well as time-fixed effects. We cluster for customer i and report results of the cluster robust regressions in ***Table 4***.

[17] Given the non-normal distribution of financial balances we run non-parametric Mann-Whitney tests for financial variables and find that current account balances (*Cash at t=0*) is significantly higher in the treatment group (mean of 4,217€ compared to 4,205€). However, this difference is economically small (12€). *Debit value at t=0* is significantly lower in the treatment group with average values of 6,995€ compared to 7,237€. We later control for these financials in regressions.

[18] Collapsing treatment periods into pre- and post-treatment is actually suggested by Bertrand, Duflo, and Mullainathan 2004 to avoid the risk of serially correlated outcomes.

Table 4: Effect of tool usage on customer financials

Dependent variable	Monthly wealth balance at the bank		Monthly debit balance		Monthly savings product balance		Monthly current account balance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interaction dummy $T_i t_j$	604.285**	256.732*	542.466**	409.025***	129.374	268.523**	437.282***	176.106*
	(0.04)	*(0.08)*	(0.02)	*(0.00)*	(0.42)	*(0.01)*	(0.00)	*(0.07)*
Dummy treatment		163.075*		171.244**		68.761		89.940
		(0.05)		*(0.03)*		*(0.12)*		*(0.18)*
Dummy monthly usage		71.751		41.792		82.459		-27.808
		(0.51)		*(0.69)*		*(0.26)*		*(0.73)*
Dummy male		73.555		165.703		-56.858		295.757***
		(0.53)		*(0.15)*		*(0.51)*		*(0.00)*
Age		15.705***		18.172***		9.881**		15.820***
		(0.01)		*(0.00)*		*(0.01)*		*(0.00)*
Dummy self-employed		1031.671		805.662		-299.592		1464.813
		(0.34)		*(0.44)*		*(0.61)*		*(0.12)*
Dummy student		-21.470		24.061		109.725		-66.888
		(0.86)		*(0.84)*		*(0.17)*		*(0.46)*
Dummy housewife		123.290		175.299		191.556		-77.837
		(0.75)		*(0.65)*		*(0.58)*		*(0.72)*
Dummy retiree		-211.077		-451.190		-23.481		-504.733*
		(0.66)		*(0.34)*		*(0.95)*		*(0.05)*
Dummy industr. worker		-355.740***		-550.917***		-43.133		-689.140***
		(0.00)		*(0.00)*		*(0.48)*		*(0.00)*
Dummy unemployed		-354.488***		-427.400***		-17.856		-543.526***
		(0.00)		*(0.00)*		*(0.72)*		*(0.00)*
Years with the bank		7.856		3.372		2.404		3.143
		(0.35)		*(0.67)*		*(0.66)*		*(0.56)*
Number of visits p.a.		-11.742		73.659		27.174		51.859
		(0.86)		*(0.18)*		*(0.49)*		*(0.12)*
Dependent financial variable at t=0 prior natural field experiment		0.962***		0.963***		0.956***		0.925***
		(0.00)		*(0.00)*		*(0.00)*		*(0.00)*
Portfolio usage		786.832**						
		(0.04)						
Saving plan		17.504		4.714		185.105**		
		(0.89)		*(0.97)*		*(0.03)*		
Saving product		1696.121***		1972.776***		1444.243***		
		(0.00)		*(0.00)*		*(0.00)*		
Retirement product		-13.516		-90.302		-3.363		
		(0.94)		*(0.60)*		*(0.98)*		
Consumer credit		-1677.357***						
		(0.00)						
Credit card		609.649***						
		(0.00)						
Mortgage		-2200.136**						
		(0.04)						

Table 4 continued

Dependent variable	Monthly wealth balance at the bank		Monthly debit balance		Monthly savings product balance		Monthly current account balance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time dummy September		-30.488		4.917		2.879		-12.385
		(0.46)		*(0.90)*		*(0.90)*		*(0.71)*
Time dummy October		182.902***		193.546***		10.965		187.790***
		(0.00)		*(0.00)*		*(0.73)*		*(0.00)*
Time dummy November		506.939***		502.875***		50.839		464.937***
		(0.00)		*(0.00)*		*(0.18)*		*(0.00)*
Time dummy December		566.667***		531.676***		55.955		471.533***
		(0.00)		*(0.00)*		*(0.32)*		*(0.00)*
Time dummy January		643.724***		601.572***		33.250		565.662***
		(0.00)		*(0.00)*		*(0.66)*		*(0.00)*
Time dummy February		558.313***		563.198***		22.527		528.640***
		(0.00)		*(0.00)*		*(0.81)*		*(0.00)*
Time dummy March		622.145***		632.548***		15.627		598.130***
		(0.00)		*(0.00)*		*(0.87)*		*(0.00)*
Constant	3502.6***	-748.2***	7462.0***	-801.0***	2771.5***	-533.1***	4482.0***	-485.8***
	0.00	*(0.00)*	0.00	*(0.00)*	0.00	*(0.00)*	0.00	*(0.01)*
Number of observations (months)	211,920	211,920	211,920	211,920	211,920	211,920	211,920	211,920
R-squared	0.0001	0.8307	0.0001	0.7298	0	0.7308	0.0002	0.632
P-value Kolmogorov –Smirnov test		*(0.41)*		*(0.00)******		*(0.00)******		*(0.00)******

Table 4 reports cluster robust DiD OLS estimates of the coefficients related to a change in monthly balances of: total wealth, which is the sum of debit less credit balance (models 1&2*)*, debit balance (models 3 & 4), pure savings product balance, i.e. monthly debit balance less any positive current account balance (models 5 & 6) and current account balance (models 7 & 8). Within this table we focus on the variable *Interaction dummy* that is equal to one if a customer from the treatment group had the tool activated in a given month. Additionally, we control for multiple other independent variables: a dummy that indicates a customer being in the treatment group (D*ummy treatment*), a dummy set to one for treatment and control group, if the given month was in the post-treatment period (*Dummy monthly usage)*, a dummy indicating men (*Dummy male)*, dummies indicating the reported job (*Dummy self-employed, Dummy student, Dummy housewife, Dummy retiree, Dummy industr. worker, Dummy unemployed*) the number of years a customer has been with the bank (*years with the bank)*¸the number of branch visits within the last 12 months *(Number of visits p.a.*), the balance of the respective dependent variable prior to the Natural Field experiment at t=0 (*Dependent financial variable at t=0 (August 2015) prior natural field experiment)*, dummies that are set to one, if a product of a specific category is owned (*Portfolio usage, Saving plan, Saving product, Retirement product, Consumer credit, Credit card, Mortgage*), time fixed-effect dummies that are set to one for each month of the observation but August 2015, ranging from September 2015 – March 2016 (*Time dummy September, Time dummy October, Time dummy November, Time dummy December, Time dummy January, Time dummy February, Time dummy March)*. *P-values are reported below coefficients in brackets. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level. R^2 values and observations in the regression are reported.* Number of observations equal 8 observed months (August 2015 – March 2016) for 26,490 customers (13,245 in treatment, 13245 in control group). In addition, we report P-values of a univariate Kolmogorov –Smirnov equality-of-distributions test (Smirnov 1933; Kolmogorov 1933), which tests equality of respective financial balance based on interaction dummy being set to one or zero.

We find that customers' average monthly wealth balance increases by 256.7 EUR, in the post-activation period. This result is significant at the 10% level in the cluster robust DiD but not robust in a non-parametric Kolmogorov–Smirnov test (Kolmogorov 1933; Smirnov 1933).

We find average customer's monthly debit balances significantly increase in the post-activation period by 409.0 EUR. This implies that customers increase their debit, i.e. savings and positive current account balances, significantly, after tool activation. This result is robust in the non-parametric Kolmogorov-Smirnov test. Also, we do find a significant increase of on average 268.5 EUR in customers' savings product balance. We are confident that the increase in monthly pure savings balance for users who activate the tool can be explained by the tool's basic functionalities. As described, within the tool the user has the opportunity to conveniently setup saving plans. These plans propose a default contribution amount that is automatically transferred to this saving plan from the current account, every month. As noted by (Thaler and Benartzi 2004), such defaults result in higher savings. Our finding is of high relevance for scientists and practitioners since it suggests that customers at least start 'putting money aside' on a savings account, after activation of the FinTech. As studies show, such mental accounting indeed has the potential to increase long term saving success (Thaler 1999; Soman and Cheema 2011; Soman and Zhao 2011). We later confirm indeed increased spending on saving plans by using transaction data.

Finally, we find a weakly significant increase in customers' monthly current account balances by on average 176.1 EUR, after tool activation. This effect is also robust in the non-parametric Kolmogorov-Smirnov test. We develop three alternative hypotheses for this observed effect – *first,* treatment customers' current account outflows might decrease because of reduced monthly spending. S*econd,* average current account inflows significantly increased. *Third,* a vice versa effect within the control group happened. With the given data, we cannot answer the third hypotheses, as we do not observe control group's individual transactions. However, in section 6 we test the first two hypotheses, by analyzing changes in consumption behavior via current account in- and outflows within the treatment group.[19,]

To summarize, our results show that the average customer indeed is affected by money management FinTech activation. In particular, she saves more money with monthly saving balance significantly increasing on average by 268 EUR in the post-treatment period. This reflects an increase by 6.9% compared to the average saving product balance of 3,832 EUR in August 2015. Total debit balance, incl. current account, increases by 409 EUR on average (+4.2% compared to pre-treatment debit

[19] Changes of monthly portfolio and credit balance are insignificant.

balance in the treatment group see ***Table 2***). We thus find evidence that a FinTech tool affects household finance and can foster saving behavior of the average customer.

Figure 1 shows the effect of money management tool activation on financials for a subgroup of treatment customers, who activated the tool in September 2015 and respective control customers. Results are qualitatively comparable to the findings for the full sample in the DiD regression. In particular, we find a strong increase in wealth, debit and savings balances in the month of activation t=1. Mean current account balances show a small increase.

5. Heterogeneity in Response to FinTech Activation?

Within this section, we assess the effect of FinTech activation on household finance for heterogeneous subgroups. *First*, we analyze the effect on customers without any previous saving activity. S*econd,* customers with existing savings in the pre-activation period are analyzed.[20] *Third,* we briefly assess the effect of FinTech activation on customers without any prior capital market participation.

5.1. Effect of tool activation on customers without prior saving activity

Within the sample of 26,490 customers, where all customers are with the bank for at least 150 days, 14,009 customers do not own a savings product in the pre-activation phase. They split 50:50 between treatment and control group (7,002 in treatment, 7,007 in control group). 13,525 of these 14,009 (96.5%) customers continue to not have a positive savings balance in the post-activation phase. However, 484 customers (3.5%) have a positive saving balance in the post-activation phase. 131 (27.1%) of them are in the control group and 353 (72.9%) are in the treatment group.

We run a robust probit analysis with Huber-White heteroscedasticity consistent standard errors and report results in ***Table 5***. The dependent dummy variable 'New savings activity' is set to one, if a customer had a positive savings account balance in the post-activation phase but did not have a positive savings account balance in the pre-activation phase. The variable is set to zero, if the customer does not have a positive savings balance throughout the complete observation period.

In ***Table 5***, we find customers who activate the tool, significantly more likely start first time saving. Marginal effects at means indicate an increase by +2.69 ppt, which is significant at the 1% level. However, coefficients for industrial employees, housewives and unemployed customers are negative and significant. We hypothesize that lack of financial interest but also ability, i.e. excess liquidity, to start saving is particularly low for these groups.

[20] We are aware that we cannot observe customers' total household wealth. We thus cannot exclude that customers did not already own a savings account at another bank. However, this is a problem, that most household finance studies face which do use empirical data, e.g., Odean 1998; Barber and Odean 2000; Schlarbaum, Lewellen, and Lease 1978.

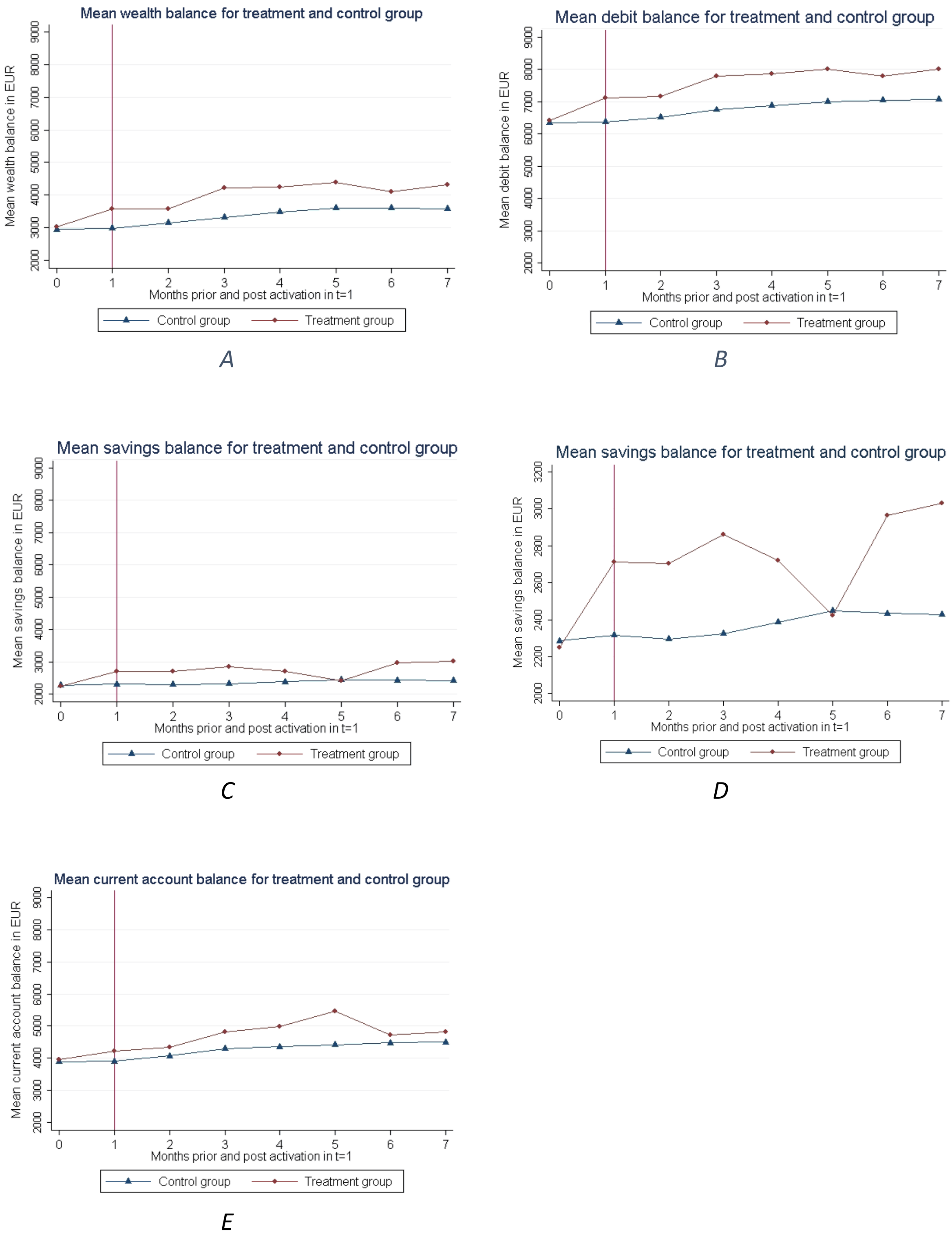


Figure 1: Mean balances of financials for treatment and control group

Panel A-E show mean balances of financials for treatment and control group prior and post tool activation at the end of each month from August 2015 (t=0) to March 2016 (t=7). The money management FinTech was activated in the first month t=1. To maximize the number of observable periods post activation, we show 3,256 matched treatment and control customers who activated the tool in September 2015. Panel A shows mean wealth of customers which is the difference between debit and credit balance. Panel B shows mean debit balances which include savings and all positive current account balances. Panel C and D (different scaling) show the increase in savings product balance for treatment and control group. Panel E shows the mean current account balance for treatment and control group.

Table 5: Probit test first time savers and first time financial market participants

	First time savings activity		First time portfolio activity	
Dependent variable	(1)	(2)	(3)	(4)
Money management tool activation	0.441***	0.453***	0.449***	0.488***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Dummy male		-0.088*		0.320***
		(0.05)		*(0.00)*
Age		-0.017*		0.231
		(0.08)		*(0.18)*
Age²		1.59E-05		-0.0002
		(0.88)		*(0.25)*
Dummy married		-0.122**		-0.072
		(0.03)		*(0.42)*
Dummy divorced		0.026		-0.121
		(0.80)		*(0.47)*
Dummy self-employed		-0.394		-0.138
		(0.31)		*(0.72)*
Dummy public employee		-0.135		-0.046
		(0.48)		*(0.83)*
Dummy industrial employee		-0.156**		-0.596***
		(0.05)		*(0.00)*
Dummy student		-0.149**		0.118
		(0.02)		*(0.31)*
Dummy housewife		-0.449**		-0.021
		(0.03)		*(0.95)*
Dummy retiree		0.526***		0.160
		(0.00)		*(0.38)*
Dummy unemployed		-0.486***		-0.414
		(0.00)		*(0.18)*
Dummy zip code 0 (East)		-0.065		0.224
		(0.54)		*(0.23)*
Dummy zip code 1 (East)		0.025		0.012
		(0.78)		*(0.95)*
Dummy zip code 2 (North)		0.081		0.229
		(0.39)		*(0.17)*
Dummy zip code 4 (West)		-0.050		0.024
		(0.58)		*(0.89)*
Dummy zip code 5 (West)		-0.001		0.000
		(0.99)		*(1.00)*
Dummy zip code 6 (South-West)		-0.042		0.365**
		(0.67)		*(0.03)*
Dummy zip code 7 (South-West)		0.073		0.330*
		(0.73)		*(0.06)*
Dummy zip code 8 (South)		0.016		0.380**
		(0.88)		*(0.03)*
Dummy zip code 9 (South-East)		-0.057		0.075
		(0.67)		*(0.76)*

Table 5 continued

Dependent variable	First time savings activity (1)	(2)	Frist time portfolio activity (3)	(4)
Length of banking relationship		0.005		0.000
		(0.13)		*(0.97)*
Intensity of banking relationship		0.143***		0.101***
		(0.00)		*(0.00)*
Current account at t=0 (August 2015)		0.000		0.000
		(0.11)		*(0.14)*
Debit value at t=0 (August 2015)				0.000***
				(0.01)
Credit value at t=0 (August 2015)		0.000**		0.000
		(0.02)		*(0.63)*
Portfolio value at t=0 (August 2015)		-3.9E-07		
		(0.29)		
Constant	-2.081***	-1.531***	-2.893***	-4.000***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Observations (customers)	14,009	14,009	24,181	24,181
Pseudo-R^2	0.026	0.0816	0.0285	0.1151

Table 5 reports probit estimates to have a positive saving balance in the post-activation phase (model 1-2), i.e. to become a first time saver, and probit estimates to have a positive portfolio balance in the post-activation phase (model 3-4). The dependent variable '*First time savings activity*' ('*Frist time portfolio activity*')is set to one, if a customer has at least one positive monthly savings (portfolio) balance in the post-activation phase but did not have any positive savings (portfolio) balance in the pre-activation phase. To estimate the probit model, we use the following independent variables: a dummy that is set to one if the customer is a man (*male),* customer age (*Age)* and squared age (*Age²*), dummies that are set to one depending on customer's relationship status (*married, divorced*), dummies which are set equal to one,. contingent on customer's reported job (*self-employed, public employee, student, housewife, retiree, unemployed*) dummies which are set to one, dependent on customer's region of living (*zip code region 0, zip code region 1, zip code region 2, zip code region 4, zip code region 6, zip code region 7, zip code region 8 and zip code region 9),* the number of years a customer has been with the bank (*Length of banking relationship*), the number of branch visits within the last 12 months (*Intensity of banking relationship*), customer's current account balance in August 2015 (*Current account at t=0),* debit balance in August 2015 (*Debit Value at t=0),* customer's credit balance in August 2015 (*Credit Value at t=0)* and customer's portfolio balance in August 2015 (*Portfolio value at t=0*).P-values are reported below coefficients in brackets. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level. Heteroscedasticity robust standard errors are used. Pseudo R^2 values and observations in the regression are reported.

5.2. Effect of tool activation on customers with prior saving activity

12,481 customers had a positive savings balance in the pre-activation period. Within this group, 6,243 customers (50.0%) were in the treatment and 6,238 (50.0%) customers in the control group. For each of these 12,481 customers, we have 8 months of observation and thus end up with a total of 99,848 observations.

We run cluster robust OLS regressions of the form stated in ***Formula 2*** to assess the effect of money management tool activation on the dependent variable '*monthly savings balance*'

Formula 2: Cluster robust DiD regression of monthly savings balances for pre-activation savers

$$Y_{i,j} = \alpha + \beta^* T_i + y^* t_j + \Omega^* T_i t_j + \Phi^* X_i + e_{i,j} \quad (2)$$

$Y_{i,j}$ is the dependent variable '*monthly saving balance*' of individual i in month j. T_i is a treatment dummy which is set to 1 if the customer is in the treatment group. t_j is a dummy variable to identify pre- and post-treatment periods (monthly usage) being set to one, if the tool was active within a given month j. The interaction variable '$T_i t_j$' is the product of T_i and t_j. It equals one for months in which customers in the treatment group had the money management tool activated and thus is our variable of interest. X_i represents demographic, banking relationship, financial control variables and time-fixed effects. We cluster for customer i.

We report results in ***Table 6***. As shown in model (2), we observe an increase of average monthly savings balance by 346.4 EUR in the post-activation phase, for the treatment group. This result is weakly significant in the cluster robust OLS regression. In models 3 & 4, we truncate outliers and exclude all customers with saving balances in August 2015 (t=0) of more than 28,317.0 EUR[21]. We test that the share of top savers is distributed equally between control and treatment group and re-run the analyses. Results are reported in models 3 & 4 in ***Table 6***. We find that the average monthly savings balance increases by 363.8 EUR for customers in the treatment group in the post activation period. The result is robust at the 5% level. We thus conclude that customers, with existing saving activities on average are *also* affected by money management tool activation and start to save more. We conclude, that the money management tool can spur both – new and existing saving activities.

5.3. Effect of tool activation on customers without prior financial market participation

Within our sample, 24,181 customers did not own a portfolio in the pre-activation phase. The split between treatment (12,122 (50.1%)) and control group (12,059 (49.9%)) is equal. Of those customers, 24,070 continue to not have a portfolio throughout our observation period. Within the group of 111 customers who open a portfolio and thereby participate in the capital market for the first time in the post-activation period, 88 (79.3%) are in the treatment group, while 23 (20.7%) are in the control group.

We run a robust probit analyses on first-time portfolio activities and report results in ***Table 5***.[22] We find a positive and significant effect (model 3&4) of FinTech activation on first time capital market participation. Yet, compared to other factors that drive capital market participation, e.g., level of education (van Rooij, Lusardi, and Alessie 2011), our identified increase (+0.34 ppt marginal effects at means) is rather small. A potential hypothesis for the observed effect is that some customers become more aware of their household financial situation, after FinTech activation. They then start to assess whether entering the financial market could be suitable. Yet in the given research design, we cannot directly observe this behavior and thus do not further pursue this finding.

[21] top 5% of savings owners in August 2015

[22] The dependent variable 'first time portfolio activity' is set to one, if a customer did not have a positive portfolio balance in the pre-activation phase but shows a portfolio balance greater than zero at least once in the post-activation phase. It is set to 0 if a customer did not have any positive portfolio balance during the complete observation phase.

Table 6: Effect of money management tool activation on customers with positive savings product balances prior experiment start

Dependent variable	Monthly savings product balance, for customers who had savings in pre-activation phase		Monthly savings product balance, for customers with savings in pre-activation phase, excl. Top 5% of Aug15 balances	
	(1)	(2)	(3)	(4)
Interaction dummy $T_i t_j$	86.2	346.357*	442.9**	363.754**
	(0.79)	*(0.08)*	*(0.03)*	*(0.05)*
Dummy treatment		146.447		61.347
		(0.11)		*(0.34)*
Dummy monthly usage		124.053		85.371
		(0.41)		*(0.50)*
Dummy male		-121.665		-133.921
		(0.47)		*(0.40)*
Age		20.148***		19.770***
		(0.01)		*(0.00)*
Dummy self employed		-489.370		-431.176
		(0.68)		*(0.23)*
Dummy student		63.366		106.803
		(0.58)		*(0.17)*
Dummy house wife		614.960		598.504
		(0.53)		*(0.55)*
Dummy retiree		-466.518		-421.172
		(0.37)		*(0.40)*
Dummy industr. worker		-110.419		-124.803
		(0.37)		*(0.21)*
Dummy unemployed		-84.992		-181.940
		(0.53)		*(0.13)*
Years with the bank		0.438		-1.350
		(0.96)		*(0.84)*
Number of visits p.a.		37.804		61.703*
		(0.48)		*(0.05)*
Dependent financial variable at t=0		0.958***		0.942***
		(0.00)		*(0.00)*
Saving plan		187.928		-354.000
		(0.63)		*(0.31)*
Saving product		1113.167***		954.472***
		(0.00)		*(0.01)*
Retirement product		-73.703		-86.952
		(0.66)		*(0.56)*
Time dummy September		0.930		115.174***
		(0.98)		*(0.01)*
Time dummy October		18.909		191.091***
		(0.78)		*(0.00)*
Time dummy November		111.816		252.677***
		(0.17)		*(0.00)*
Time dummy December		136.984		318.336***
		(0.24)		*(0.00)*
Time dummy January		62.483		319.758***
		(0.67)		*(0.01)*
Time dummy February		58.919		354.299***
		(0.75)		*(0.02)*
Time dummy march		26.152		369.284***
		(0.89)		*(0.02)*
Constant	5847.8***	-951.3**	2686.0***	-465.5
	(0.00)	*(0.02)*	*(0.00)*	*(0.13)*
Number of observations (months)	99,848	99,848	94,848	94,848
R-squared	0	0.7509	0.0003	0.2134

Table 6 *reports cluster robust DiD OLS regression results for monthly balances of: savings products for customers who had at least one positive saving balance in the pre-activation period (models 1&2), and for customers with positive savings balances but below 28,317 EUR (top 5% in August 2015) (models 3&4). Within this table we focus on the variable 'Interaction dummy' which equals one, if a customer in the treatment group had the tool activated in a given month. We control for: customers being in the treatment group (Dummy treatment),* a dummy set to one for treatment and control group, if the given month was in the post-treatment period *(Dummy monthly usage*), a dummy indicating men *(Dummy male*), dummies indicating the reported job *(Dummy self-employed, Dummy student, Dummy housewife, Dummy retiree, Dummy industr. worker, Dummy unemployed)* number of years a customer has been with the bank *(years with the bank)*¸the number of branch visits within the last 12 months (*Number of visits p.a.),* the balance of the respective dependent variable prior to the Natural Field experiment at t=0 *(Dependent financial variable at t=0 (August 2015),* dummies that are set to one, if a product of a specific category is owned *(Saving plan, Saving product, Retirement product),* time fixed-effect dummies that are set to one for each month of the observation. P-values are reported below coefficients in brackets. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level. R^2 values and observations in the regression are reported. *Number of observations equal 8 observed months (August 2015 – March 2016).*

6. Does Customer Income and Spending Behavior Change Post Activation?

As reported in model 8 of ***Table 4***, we found that the average monthly current account balance weakly significantly increases by 176.1 EUR for the treatment group in the post-activation period. By analyzing individual transactions of the treatment group, we provide further evidence for changes in consumption behavior post activation[23]. We *first* run within subject event studies on monthly spending per category. *Second*, we focus on the observed increase in salary inflows. *Third*, we assess the identified increase in spending for saving and investments. *Fourth*, we test whether customers sustainably use the tool.

6.1. Within subject event studies on monthly spending and income categories

Once activated, the tool automatically categorizes transactions of the past months. This means, for every new FinTech user, inflow and outflow transactions of previous months, in which the money management tool was not used, are analyzed, too. Given this data structure, we run multiple within subject event studies, as discussed, e.g., by MacKinlay 1997 and recently applied by, e.g., Gerhardt and Hackethal 2009, in a comparable design.

First, we set our event window to one month prior tool activation (t-1) and one month post activation (t+1)[24]. We analyze monthly spending/income for each of the 12 main categories in these months. As described in ***Table 1***, we can observe all transactions of customers in the treatment group between October 1st 2015 and March 31st 2016. Since the planned within subject event study requires to have at least one month prior and one month post tool activation, we use a subset of 10,115 customers who enrolled between November 1st 2015 and February 29th 2016[25]. Results of a univariate t-test, a non-parametric Mann-Whitney test, and a cluster robust OLS regression are reported in ***Table 7***[26].

[23] The observed difference could also be driven by changes in the control group. However, given the research design, we cannot observe control group's individual transactions but only monthly balances.

[24] We choose a comparison on monthly basis, since households typically budget their income and expenses on a monthly basis (Thaler 1999).

[25] Customers activated the tool within these months as follows: 1,368 in November 2015, 2,785 in December, 2,928 in January 2016, 3,034 customers in February 2016. Given the data structure, the necessity to work with a subsample does not allow to fully match the observed difference-in-difference increase of average monthly current account balance by 176.1 EUR.

[26] We run a skewness and kurtosis test for normality as suggested by (D'agostino, Belanger, and D'agostino, JR 1990) and find that none of the monthly spending/income categories is normally distributed. As this limits the precision of the univariate t-test, this test is only reported for completion.

The OLS regression has the following form.

Formula 3: Cluster robust OLS regressions of current accounts' monthly outflows/inflows per category

$$Y_{i,t} = \alpha + \beta^*T_t + \Phi^*X_i + e_{i,t} \tag{3}$$

With $Y_{i,t}$ being the monthly sum of category Y for customer i at time t (month prior/after tool activation), and T_t being the treatment dummy which is set to one in the post-activation period. X_i refers to multiple control variables for gender, marital and employment status, region of living, length of banking relationship, number of annual branch visits, types of banking products owned, month of tool activation as well as current account, debit and credit balances prior to the natural field experiment.[27] We cluster for customer i.

In **Table *7***, three findings of economic relevance are significant in both the non-parametric test and the cluster robust OLS regression.[28] We find an increase in wage and salary inflows on average by 413 EUR.[29] Spending on savings and investment activities surge significantly by 284 EUR. Non-categorized outflows rise significantly by 369 EUR between t-1 and t+1. We discuss these findings in the following. Other changes to consumption behavior were either not significant or not of economic relevance.

6.2. Observed increase in salary income

As we aim to explain what drives the increase in observed salary increase in ***Table 7*** between t-1 and t+1, we first identify all salary, wage, or pension inflow transactions.[30] Next, we classify which transaction occurred in the pre- or post-activation period. We find that 6,937 out of 10,115 customers (68.6%) had salary inflows prior to money management tool activation, while 2,621 customers (25.9%) did not have any salary inflows during the observed period. 557 customers (5.5%) did not have any salary inflow prior tool activation, but had salary inflows, after tool activation. Yet, 333 out of the 557 customers received unemployment or comparable support. To be more conservative, we treat them as customers with previous salary inflow. Thus we end up with 7,270 customers with previous 'salary-alike' inflows and 224 customers (2.2%) with first time salary inflow post activation. This share of 2.2% is significant in bot a t-test and a binomial test.

[27] Regression results for each category are available upon request.
[28] The increase in insurance inflows and decrease in children related inflows is driven by a technical error in the algorithm, resulting in wrong allocation of governmental child support. We exclude this effect from discussions.
[29] To ensure, that the results of the initially conducted DiD analysis (*Table 4*) were not biased by customers who have first time salary inflows, we re-run cluster robust winsorized DiD for the subgroup of 7,270 customers with salary alike inflows prior to activation and respective control customers. Results are reported *in Appendix D.* We again find a significant increase in monthly debit and savings balances.
[30] To facilitate reading, we will jointly refer to these three types of income as 'salary income'.

Table 7: Current account inflows and outflows by main category one month prior and one month post money management tool activation

Spending per category, in €	Month prior money management tool activation (t-1)			Month post money management tool activation (t+1)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
				Inflows						
All inflows	4,236.71	2,209.26	10,115	4,722.20	2,277.74	10,115	.02	.00	.01	485.49***
Wage and salary income	3,307.71	1,796.34	10,115	3,721.00	1,846.16	10,115	.03	.00	.02	413.30***
Cost of living related inflows	16.64	0.00	10,115	15.26	0.00	10,115	.81	.05	.61	-1.38
Rental income	27.11	0.00	10,115	34.57	0.00	10,115	.35	.00	.28	7.46
Leisure and travel related inflows	13.30	0.00	10,115	17.97	0.00	10,115	.24	.08	.06	4.67*
Mobility related inflows	10.74	0.00	10,115	11.38	0.00	10,115	.89	.32	.84	0.64
Medical related inflows	10.63	0.00	10,115	7.72	0.00	10,115	.26	.65	.18	-2.91
Children related income	30.92	0.00	10,115	4.15	0.00	10,115	.00	.00	.00	-26.77***
Education related inflows	18.25	0.00	10,115	21.36	0.00	10,115	.75	.07	.68	3.11
Saving & investment income	152.79	0.00	10,115	181.23	0.00	10,115	.33	.01	.09	28.44*
Insurance inflows	197.97	0.00	10,115	249.87	0.00	10,115	.00	.00	.00	51.89***
Credit related inflows	16.32	0.00	10,115	38.40	0.00	10,115	.08	.46	.08	22.08
Other inflows (incl. cash)	434.34	0.00	10,115	419.29	0.00	10,115	.69	.00	.57	-15.05
				Outflows						
All outflows	-4,009.53	-2,156.49	10,115	-4,862.60	-2,322.01	10,115	.00	.00	.00	-853.07***
Non categorized outflows	-1,518.87	-333.70	10,115	-1,888.48	-398.73	10,115	.00	.00	.00	-369.61***
Cost of living	-272.44	-163.89	10,115	-267.68	-164.54	10,115	.69	.07	.63	4.76
Residential expenses	-401.65	-185.00	10,115	-425.62	-227.81	10,115	.14	.00	.00	-23.97***
Leisure and travel expenses	-75.27	0.00	10,115	-72.92	-5.95	10,115	.71	.02	.69	2.35
Mobility expenses	-80.26	-6.90	10,115	-94.44	-13.00	10,115	.19	.01	.15	-14.18
Medical expenses	-22.41	0.00	10,115	-32.07	0.00	10,115	.02	.00	.02	-9.66***
Children related outflows	-8.84	0.00	10,115	-7.99	0.00	10,115	.51	.10	.17	0.85
Education and work costs	-19.30	0.00	10,115	-26.68	0.00	10,115	.00	.00	.00	-7.38***
Saving & investment outflows	-159.78	0.00	10,115	-444.35	0.00	10,115	.01	.00	.01	-284.57***
Insurance expenses	-262.84	-55.36	10,115	-271.29	-69.22	10,115	.44	.00	.28	-8.44
Credit down payments	-167.05	0.00	10,115	-185.25	0.00	10,115	.22	.01	.17	-18.19
Other outflows (incl. cash)	-1,020.83	567.79	10,115	-1,145.83	-600.00	10,115	.00	.00	.00	-125.00***

Table 7 reports sum of monthly income and spending per money management tool category. The columns '*Month prior tool activation (t-1)*' and '*Month post tool activation (t+1)*' show mean and median values per category. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in formula 3.

We would like to stress again that all customers in this sample, were with the bank for at least 210 days by October 1st 2015. We thus can exclude that these customers are new banking customers, who move accounts at customer relationship initiation. Also, to exclude that the effect is driven by young job starters, we re-run the analysis, excluding all customers below the age of 31 from the sample of the 10,115 customers. The share of customers with first time salary inflows post tool activation still remains highly significant.[31] This supports the hypotheses that it is indeed the money management tool activation which drives new salary inflows and not a specific demographic group.[32]

Instead we hypothesize that these customers start using the money management tool and then move salary transactions to our cooperating bank. We search for evidence that these 224 new salary customers use the tool more intensively than the 2,621 customer who continue to not have salary inflows post activation. We use the number of manual re-categorizations and the usage of the budgeting feature within the tool as proxy for usage intensity. We run 2 robust probit regressions, with being in the top quartile of re-categorizations, and having activated the budgeting function, being the dependent variables. We control for customer demographics, banking relationship, initial financial situation and month of tool activation. Results indicate that customers who have new salary inflows post activation also are more likely to be in the top quartile of re-categorizations and have the budgeting function activated, compared to customers without salary inflows. However, results are not significant. We hypothesize that the lack of significance could be driven by too little statistical power, given the smaller sample size.[33]

To summarize, in the DiD regression analysis of ***Table 4***, we found a statistically significant increase of average monthly current account balances in the post-activation phase within the treatment group. By running a within-subject event study for a subset, we find that a significant share of customers who activate the tool have salary inflows post tool activation for the first time in the observation period. We show that results are robust even after removing a group of potential job starters. We also can exclude that the observed behavior is driven by new customers, which could explain this effect, too. In the increasingly competitive retail banking segment (Clerides, Delis, and Kokas 2015), a FinTech that could more intensively engage 2.2% of its users (7.9% of all previous non-salary users) with the providing financial institution could be of tremendous value for practitioners. This finding confirms opinions expressed by practitioners, and affirms their hypotheses that money management FinTechs can play a key differentiating role for banks that offer this service (Früchtl and Peters 2014). In line

[31] In particular, 114 out of 7,442 customers (1.5%), aged 31 or older, have first time salary inflows post tool activation.
[32] Yet, this analysis is still contingent on the validity of the money management tool algorithm.
[33] Analyses available upon request.

with (Kumar 2016), we take this as opportunity to stress the relevance of research on FinTechs also for practitioners.

6.3. Observed increase in savings and investment outflows

In the within subject analysis in ***Table 7***, we find that spending on savings and investment products increases significantly by 284.57 EUR after activation (t-1 compared to t+1). To gain additional insights on the behavior driving this effect, we run within subject event studies for the sub-categories of savings & investment outflows, one month prior compared to one month post activation. Results are reported in ***Table 8***.

Table 8: Monthly spending within sub-category 'saving & investment' 1 month post compared to 1 month prior FinTech activation

Spending per sub-category, in €	Month prior tool activation (t-1)			Month post tool activation (t+1)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
Savings and Investment outflows										
All savings and investment outflows	-159.78	0.00	10,115	-444.35	0.00	10,115	.01	.00	.01	-284.57***
Retirement savings	-4.42	0.00	10,115	-4.08	0.00	10,115	.78	.89	.73	0.33
Mortgage savings	-47.95	0.00	10,115	-36.04	0.00	10,115	.34	.18	.34	11.91
Money market and savings account	-7.02	0.00	10,115	-18.78	0.00	10,115	.17	.42	.15	-11.76
Securities investments	-73.73	0.00	10,115	-330.47	0.00	10,115	.02	.06	.02	-256.74*
Saving plan	-25.74	0.00	10,115	-53.10	0.00	10,115	.00	.00	.00	-27.37***
Other investments	-0.93	0.00	10,115	-1.88	0.00	10,115	.30	.84	.28	-0.95

Table 8 reports sum of monthly spending per sub-category of savings & investment category. The columns '*Month prior tool activation (t-1)*' and '*Month post tool activation (t+1)*' show mean and median values per sub-category. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in formula 3.

We find a statistically significant increase of contributions to saving plans on average by 27.37 EUR. Also, we do find that outflows for securities investments increase by 256.74 EUR. This increase is significant in the multivariate test, but only weakly significant in the non-parametric Mann-Whitney test. To test, whether the observed increase in outflows for saving plans and securities investment are sustainable over time, we run another within-subject analysis, comparing one month prior (t-1) to *two* months post activation (t+2). As this requires, to have at least 2 observations available in the post-activation phase, we take a subsample of 7,081 customers who registered between November 1st 2015 and January 31st 2016. Results are reported in ***Table 9***[34].

[34] We also compare the subsample's overall inflow and outflow transactions, one month prior and one month after tool activation. We find qualitatively comparable results to Table 7 although the observed increase in salary income is not significant any more. We hypothesize that this is driven by a lack of power, given subsample size. Results are shown in Appendix E.

Table 9: Monthly spending within sub-category 'saving and investment' 2 months post compared to 1 month prior FinTech activation

Spending per sub-category, in €	Month prior tool activation (t-1)			2nd month post tool activation (t+2)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
Savings and Investment outflows										
Saving & investment outflows	-178.66	0.00	7,081	-168.23	0.00	7,081	.78	.03	.77	10.43
Retirement savings	-5.53	0.00	7,081	-13.58	0.00	7,081	.37	.70	.37	-8.05
Mortgage savings	-54.06	0.00	7,081	-31.99	0.00	7,081	.20	.20	.20	22.06
Money market and savings account	-6.97	0.00	7,081	-3.78	0.00	7,081	.14	.84	.12	3.19
Securities investments	-84.44	0.00	7,081	-74.34	0.00	7,081	.74	.67	.72	10.10
Saving plan	-26.62	0.00	7,081	-43.06	0.00	7,081	.07	.01	.07	-16.44*
Other investments	-1.05	0.00	7,081	-1.48	0.00	7,081	.29	.66	.02	-0.44**

Table 9 reports sum of monthly spending per sub-category of savings & investment category. The columns '*Month prior tool activation (t-1)*' and '2nd m*onth post tool activation (t+2)*' show mean and median values per sub-category one month prior tool activation and the second month after tool activation. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in in formula 3.

We do find that the increase in savings plan contribution is sustainable over a period of 2 months. The mean difference declines slightly to -16.44 EUR, however, the difference remains significant in the cluster robust OLS regression and the Mann-Whitney test. On the other hand, spending for securities is not significantly different any more after two months, i.e. it is not sustainable[35].

These observations are in line with the results in ***Table 4***, where we found a significant difference in treatment customers' debit and savings product balances but not in portfolio value. We conclude that the customers use the money management tool's saving function, which allows to easily set new saving targets and monthly contribution rates. A minority of customers shows increased security investment activities, which are, however, not persistent over time.

6.4. Observed increase of non-categorized items

The third observation made in ***Table 7*** was an increase of non-categorized outflows by on average 369 EUR, which was significant at the 1% level. As the algorithm's precision did not decrease during our observation period and it is impossible to manually allocate a transaction into the non-categorized group, two alternative hypotheses could explain the observation. *First,* there was a significant increase in transactions with parties that were unknown to the algorithm. *Second,* customers' manual re-allocation activity of non-categorized items has declined, in the first month after activation.

First, the number of transactions with unknown parties could increase for two reasons. The effect could be driven by customers who made the account their salary account and as a consequence also had many new transactions. To test this hypothesis, we take the subsample of 6,937 customers who

[35] We achieve qualitatively comparable results, if we run this analysis only for customers with previous salary inflows.

had a real salary inflow prior to tool activation and run a within subject event study, again with an event window of the month post activation t+1 and the month prior activation t-1. Results are reported in Appendix F. We again find a significant increase in non-categorized outflows. We thus reject the hypothesis, that the effect is only driven by new salary customers.

Another potential explanation for an increasing number of unknown transactions could be, that all customers start to purchase in very different ways after tool activation[36]. While we cannot completely rule out this explanation with the given data, we believe that this behavioral change is very unlikely, especially given the sample size and demographic breadth of customers. We thus conclude that the increase in non-categorized transactions is not driven by an increase of transactions with unknown parties.

Secondly, the increase in non-categorized transactions could be driven by a decline in customers' discipline to manually re-allocate non-automatically-categorized transactions. As explained, at tool initiation, customers have the opportunity to review non-categorized transactions of the past 6 months and allocate them, correctly. We hypothesize that customers do this once for past transactions during an initiation period of the tool, but then lack the discipline to do this over the next months. Thereby they sacrifice the precision of the analyses. If our hypothesis was right, we first would not find an additional increase between future months (t+1 compared to t+2) and secondly, we would see that customers who most actively use the tool do not show this effect.

As an initial step we run a within subject analysis on monthly categorical spending in t+1 and t+2 for the subsample of 7,081 customers who registered between November 1st 2015 and January 31st 2016. Results are reported in Appendix G. We find no significant increase in non-categorized spending between first month (t+1) and second month (t+2) post money management tool activation. This is evidence that the effect, leading to the increase in non-categorized costs, is rather driven by an overly precise allocation of past transactions in t-1 and not by a worse allocation of transactions in t+1.

Vice versa this is also evidence, that the majority of customers shows some initial interest and manually allocates past non-categorized transactions (incl. those for month t-1) but loses interest or self-discipline to continue with this behavior already after the first month.

7. Conclusion

Does new financial technology (FinTech) such as money management tools affect household finance and saving behavior in particular? To address this question, we cooperate with a large European retail

[36] The algorithm has a high precision for German market's most relevant retailing companies. If, however, customers would start to purchase only at unknown transaction partners, the algorithm's precision could suffer.

bank and analyze data from a large natural experiment in which customers receive an invitation to activate the bank's money management FinTech. We assess what happens to customers' household finance and saving behavior, after they activate the bank's proprietary FinTech service. We make the following findings.

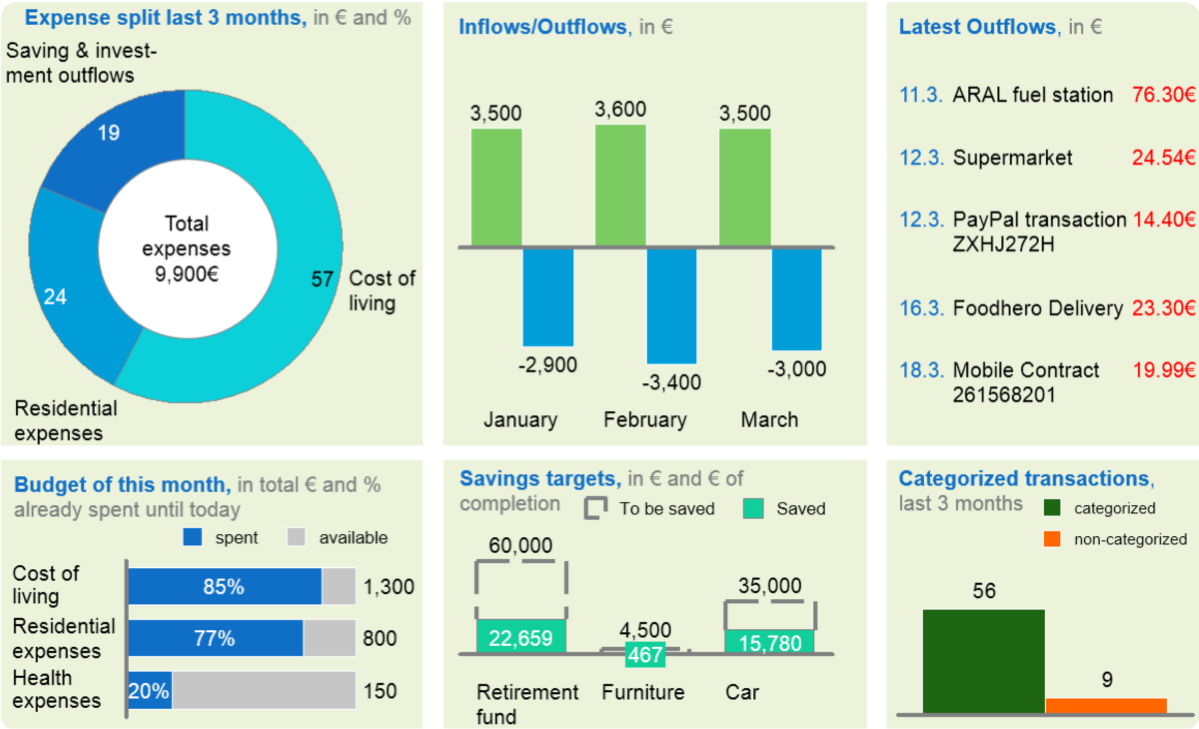
First, we find that customers who are male, young, have low saving balances prior to the experiment and possess some basic financial knowledge, are most likely to activate the FinTech. Customers with lower financial education are less likely to activate the FinTech. Second, if the FinTech is activated, we find that customers' average savings increase significantly and with economically relevant (+268 EUR +6.9ppt), compared to a control group that does not activate the FinTech. We also find a significant increase of current account balances. Third, we show that also customers without any previous saving activity are more likely to start first time saving and even first time capital market participation, after tool activation. Fourth, while we do not find any other economically relevant change in consumption behavior, we find evidence that the increase in average current account balances is driven by a smaller set of customers who have first time salary inflows, after tool activation. We can exclude that these customers are new customers, or that the effect is driven by first-time job-starters. Furthermore, analyses of individual transactions identify increased spending on saving plans – a feature implemented within the money management FinTech. This is in line with the observed increase in monthly savings balances. Finally, we find evidence that the majority of customers does not use the money management tool in a disciplined way over several months. For most customers, the money management tool's saving feature is thus of high relevance. The savings function works with a default approach and transfers money into a physically existing 'mental account'. Previous studies have shown that this approach is indeed very successful to start accumulating wealth (Thaler 1999; Thaler and Benartzi 2004). Overall, our results suggest that FinTechs such as money management tools indeed can affect personal finance and increase household savings.

In a period of rapidly growing valuations and dispersion of FinTechs (Statista 2017), our results contribute to academia, regulators and practitioners. For researchers, we demonstrate that FinTechs indeed have the potential to affect household finance and saving behavior in particular. Thus, FinTechs could provide new dynamics and high quality data for the research streams of consumption lifecycle hypothesis (Modigliani and Brumberg 1954), intertemporal choice (Loewenstein and Thaler 1989), reaction to income shocks (Cocco, Gomes, and Maenhout 2005; Polkovnichenko 2007) and individual's saving behavior (Beshears et al. 2015; Thaler and Benartzi 2004). Regulators can build on the result that FinTech Services, which may also be offered by banking incumbents to their customers, indeed can increase saving rates. They thus might want to foster FinTechs' technological development and stimulate the dispersion of these tools. We also hope to contribute to practitioners' discussion by showcasing that a bank-proprietary FinTech can encourage customers to transfer first time salary inflows to the cooperating bank after tool activation, which is of tremendous value in today's hyper-competitive retail-banking environment.

However, we also see the need for further research. As we found that customers without previous financial knowledge are hardly attracted by FinTechs, experimenting with innovative ways to offer FinTech solutions to these customers and increase the acceptance rate by this group could be of scientific and regulatory interest. Also, testing new approaches to overcome the drop of interest in actively managing household financials already in the first month post FinTech activation, should be on the agenda of researchers and practitioners.

Appendix

Appendix A: Money management tool starting page (simplified)



Appendix A shows a disguised, simplified example of the cooperating bank's money management tool. On the top left, spending per main category (see Table 7) are displayed. Below, monthly budgets and this month's usage per outflow category are shown. This is pre-populated based on past spending but the customer can individually adjust each budget. The top center box shows inflows and outflows over the last months. The bottom center element includes saving targets and completion status, which the customer can easily setup. Top right are latest outflow transactions, while the bottom right box shows number of categorized and non-categorized transactions. By clicking on each box, additional analyses or management features are available. The tool can be accessed online or via the mobile banking app and is free of charge for customers.

Appendix B: Descriptive statistics on matched and non-matched customers in control group

		Selected for matching			Not selected for matching			t-test	Mann-Whitney test
Data variable	Measurement units	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value
		Client demographics							
Gender	Dummy=1 if male	58.9%	1	13,245	62.4%	1	425	.15	.15
Age	Years	38.8	36.0	13,245	38.7	35.0	425	.86	.86
Age 0-15	Dummy=1 if Age 0-15	0.0%	0	13,245	0.1%	0	1,832	.18	.18
Age 16-25	Dummy=1 if Age 16-25	15.3%	0	13,245	5.6%	0	1,832	.00	.00
Age 26-40	Dummy=1 if Age 26-40	47.1%	0	13,245	8.7%	0	1,832	.00	.00
Age 41-50	Dummy=1 if Age 41-50	19.5%	0	13,245	3.7%	0	1,832	.00	.00
Age 51-65	Dummy=1 if Age 51-65	12.8%	0	13,245	3.6%	0	1,832	.00	.00
Age 65plus	Dummy=1 if Age 65plus	5.3%	0	13,245	1.5%	0	1,832	.00	.00
Joint account	Dummy=1 if Joint account	0.0%	0	13,245	76.8%	0	1,832	.00	.00
Single	Dummy=1 if single	55.5%	1	13,245	11.1%	0	1,832	.00	.00
Civil union	Dummy=1 if in civil union	0.2%	0	13,245	0.1%	0	1,832	.16	.16
Married	Dummy=1 if married	33.8%	0	13,245	8.0%	0	1,832	.00	.00
Separated	Dummy=1 if separated	1.8%	0	13,245	1.1%	0	1,832	.03	.03
Divorced	Dummy=1 if divorced	6.3%	0	13,245	2.2%	0	1,832	.00	.00
Widowed	Dummy=1 if widowed	2.0%	0	13,245	0.5%	0	1,832	.00	.00
No marriage reported	Dummy=1 if nothing reported	0.4%	0	13,245	76.9%	1	1,832	.00	.00
Self-employed	Dummy=1 if self-employed	0.7%	0	13,245	1.9%	0	1,832	.00	.00
Employees	Dummy=1 if employee	43.1%	0	13,245	8.6%	0	1,832	.00	.00
Public employees	Dummy=1 if public employee	2.3%	0	13,245	0.3%	0	1,832	.00	.00
Industrial worker	Dummy=1 if industrial worker	9.9%	0	13,245	3.7%	0	1,832	.00	.00
Students	Dummy=1 if student	22.0%	0	13,245	3.3%	0	1,832	.00	.00
Housewife	Dummy=1 if housewife	2.3%	0	13,245	1.2%	0	1,832	.00	.00
Retiree	Dummy=1 if retiree	3.7%	0	13,245	1.7%	0	1,832	.00	.00
Unemployed	Dummy=1 if unemployed	4.2%	0	13,245	1.4%	0	1,832	.00	.00
No job reported	Dummy=1 if nothing reported	11.7%	0	13,245	77.9%	1	1,832	.00	.00
Zip code region 0 (East)	Dummy=1 if zip code starts with 0	7.7%	0	13,245	7.5%	0	1,832	.75	.75
Zip code region 1 (East)	Dummy=1 if zip code starts with 1	14.2%	0	13,245	11.4%	0	1,832	.00	.00
Zip code region 2 (North)	Dummy=1 if zip code starts with 2	12.1%	0	13,245	11.0%	0	1,832	.17	.17
Zip code region 3 (Central)	Dummy=1 if zip code starts with 3	7.9%	0	13,245	7.4%	0	1,832	.46	.46
Zip code region 4 (West)	Dummy=1 if zip code starts with 4	16.9%	0	13,245	19.9%	0	1,832	.00	.00
Zip code region 5 (West)	Dummy=1 if zip code starts with 5	10.7%	0	13,245	12.1%	0	1,832	.08	.08
Zip code region 6 (South-West)	Dummy=1 if zip code starts with 6	10.6%	0	13,245	9.5%	0	1,832	.13	.13
Zip code region 7 (South-West)	Dummy=1 if zip code starts with 7	8.1%	0	13,245	9.3%	0	1,832	.08	.08
Zip code region 8 (South)	Dummy=1 if zip code starts with 8	7.2%	0	13,245	7.3%	0	1,832	.87	.87
Zip code region 9 (South-East)	Dummy=1 if zip code starts with 9	3.8%	0	13,245	3.7%	0	1,832	.85	.85

Appendix B continued

Data variable	Measurement units	Selected for matching Mean (A)	Median	N	Not selected for matching Mean (B)	Median	N	t-test P-Value	Mann-Whitney test P-Value
		Bank relationship							
Length of banking relationship	Years	12.5	9.6	13,245	10.8	8.6	1,819	.00	.00
Intensity of banking relationship	# of branch visits p.a.	0.9	0.0	13,245	1.8	1.0	1,832	.00	.00
Saving plan	Dummy=1 if 'Saving plan' owned	41.1%	0	13,245	41.2%	0	1,832	.93	.93
Saving product	Dummy=1 if 'Saving product' owned	13.3%	0	13,245	20.6%	0	1,832	.00	.00
Retirement product	Dummy=1 if 'Retirement product' owned	26.6%	0	13,245	10.9%	0	1,832	.00	.00
Credit card	Dummy=1 if 'Credit card' owned	15.5%	0	13,245	16.5%	0	1,832	.29	.29
Consumer credit	Dummy=1 if 'Consumer credit' owned	8.1%	0	13,245	15.6%	0	1,832	.00	.00
Mortgage	Dummy=1 if 'Mortgage' owned	2.3%	0	13,245	18.1%	0	1,832	.00	.00
Credit default risk	Bank credit score (0=low - 1=high)	0.009	0.003	13,245	0.010	0.005	1,832	.00	.00
		Financials							
Cash at t=0 (August 2015)	€	4,217	1,046	13,245	15,525	1,943	1,832	.00	.00
Share of portfolio owners	Dummy=1 if portfolio is owned	9.7%	0	13,245	15.0%	0	1,832	.00	.00
Portfolio value at t=0 (August 2015)	€, if depot is owned	46,734	6,336	1,280	157,074	29,779	274	.00	.00
Debit value at t=0 (August 2015)	€	6,955	1,336	13,245	29,122	2,747	1,832	.00	.00
Credit value at t=0 (August 2015)	€	3,716	0	13,245	31,619	0	1,832	.00	.00

Appendix B reports summary statistics on customer demographics, bank relationship variables and financial balances of matched and non-matched customers in the treatment group. The columns 'Selected for matching' and 'Not selected for matching' show means, median values and quantity of observations for each group. Next, we report p-values of a univariate t-test on difference of means and p-values of a univariate Mann-Whitney test, which does not require a normally distributed sample. Customer demographics include information on the proportion of male customers (*Gender*), customers' age (*Age),* and respective distribution between age groups (*Age 0-15, Age 16-25, Age 26-40, Age, 41-50, Age 51-65, Age 65 plus*). *Joint account* identifies share of accounts in each group that are owned by more than one person. Distribution between the groups of marital status is reported in the variables *Single, Civil Union, Married, Separated, Divorced, Widowed* based upon customers' reported status. If the status was not provided, *No marriage reported* was set to 1. *Employee, house wife, retiree, unemployed, public employee,* and *industrial employee* report customers' employment status. *Self-employed* includes customers who work as executives or owner of a firm, while *student* includes (high school) pupils, regular students and pupils of technical apprenticeships. *No job reported* identifies customers who did not provide a job information. We use customers' registration address' first zip code number to identify their region of living (*Zip code region 0-9).*We report the number of years, a customer was with the bank (*length of relationship)* and the *intensity of relationship*, measured as the number of branch visits within the last 12 months. We report whether a customer owns at least one product from a specific product category (*Saving plan, Saving product, Retirement product, Credit card, Consumer credit, Mortgage, Portfolio owned).* The bank's internal risk score (*credit default risk)* ranges from 0 (low) to 1 (high). We compare customers' initial balances on August 31st 2015 (t=0) for current account (C*ash at t=0)*, deposits (*Debit value at t=0*) and overall borrowings (*Credit value at t=0*). Portfolio values before Field Experiment (*Portfolio value at t=0)* are reported, too if a portfolio is owned.

Appendix C: Descriptive statistics on matched treatment and control group

Data variable	Measurement units	Natural field experiment treatment group			Natural field experiment control group			t-test	Mann-Whitney test
		Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value
		Client demographics							
Gender	Dummy=1 if male	58.9%	1	13,245	58.9%	1	13,245	1.00	
Age	Years	38.8	36.0	13,245	38.8	36.0	13,245	.96	
Age 0-15	Dummy=1 if Age 0-15	0.0%	0	13,245	0.0%	0	13,245	1.00	
Age 16-25	Dummy=1 if Age 16-25	15.3%	0	13,245	15.3%	0	13,245	1.00	
Age 26-40	Dummy=1 if Age 26-40	47.1%	0	13,245	47.1%	0	13,245	1.00	
Age 41-50	Dummy=1 if Age 41-50	19.5%	0	13,245	19.5%	0	13,245	1.00	
Age 51-65	Dummy=1 if Age 51-65	12.8%	0	13,245	12.8%	0	13,245	1.00	
Age 65plus	Dummy=1 if Age 65plus	5.3%	0	13,245	5.3%	0	13,245	1.00	
Joint account	Dummy=1 if Joint account	0.0%	0	13,245	0.0%	0	13,245	1.00	
Single	Dummy=1 if single	55.5%	1	13,245	55.5%	1	13,245	1.00	
Civil union	Dummy=1 if in civil union	0.2%	0	13,245	1.6%	0	13,245	.38	
Married	Dummy=1 if married	33.8%	0	13,245	33.8%	0	13,245	1.00	
Separated	Dummy=1 if separated	1.8%	0	13,245	1.8%	0	13,245	.71	
Divorced	Dummy=1 if divorced	6.3%	0	13,245	6.3%	0	13,245	.91	
Widowed	Dummy=1 if widowed	2.0%	0	13,245	1.9%	0	13,245	.75	
No marriage reported	Dummy=1 if nothing reported	0.4%	0	13,245	0.5%	0	13,245	.39	
Self-employed	Dummy=1 if self-employed	0.7%	0	13,245	0.7%	0	13,245	1.00	
Employees	Dummy=1 if employee	43.1%	0	13,245	43.1%	0	13,245	.92	
Public employees	Dummy=1 if public employee	2.3%	0	13,245	2.3%	0	13,245	.93	
Industrial worker	Dummy=1 if industrial worker	9.9%	0	13,245	9.9%	0	13,245	1.00	
Students	Dummy=1 if student	22.0%	0	13,245	22.0%	0	13,245	1.00	
Housewife	Dummy=1 if housewife	2.3%	0	13,245	2.3%	0	13,245	1.00	
Retiree	Dummy=1 if retiree	3.7%	0	13,245	3.7%	0	13,245	1.00	
Unemployed	Dummy=1 if unemployed	4.2%	0	13,245	4.2%	0	13,245	1.00	
No job reported	Dummy=1 if nothing reported	11.7%	0	13,245	11.7%	0	13,245	.84	
Zip code region 0	Dummy=1 if zip code starts with 0	7.7%	0	13,245	7.7%	0	13,245	.94	
Zip code region 1	Dummy=1 if zip code starts with 1	14.2%	0	13,245	14.0%	0	13,245	.56	
Zip code region 2	Dummy=1 if zip code starts with 2	12.1%	0	13,245	12.0%	0	13,245	.69	
Zip code region 3	Dummy=1 if zip code starts with 3	7.9%	0	13,245	8.0%	0	13,245	.73	
Zip code region 4	Dummy=1 if zip code starts with 4	16.9%	0	13,245	17.2%	0	13,245	.56	
Zip code region 5	Dummy=1 if zip code starts with 5	10.7%	0	13,245	10.9%	0	13,245	.73	
Zip code region 6	Dummy=1 if zip code starts with 6	10.6%	0	13,245	10.4%	0	13,245	.49	
Zip code region 7	Dummy=1 if zip code starts with 7	8.1%	0	13,245	7.7%	0	13,245	.19	
Zip code region 8	Dummy=1 if zip code starts with 8	7.2%	0	13,245	7.2%	0	13,245	.92	
Zip code region 9	Dummy=1 if zip code starts with 9	3.8%	0	13,245	4.1%	0	13,245	.19	

Appendix C continued

Data variable	Measurement units	Natural field experiment treatment group Mean (A)	Median	N	Natural field experiment control group Mean (B)	Median	N	t-test P-Value	Mann-Whitney test P-Value
		Bank relationship							
Length of banking relationship	Years	12.5	9.6	13,245	12.5	9.6	13,245	.74	
Intensity of banking relationship	# of branch visits p.a.	0.89	0.0	13,245	0.86	0.0	13,245	.27	
Saving plan	Dummy=1 if 'Saving plan' owned	41.1%	0	13,245	41.1%	0	13,245	.95	
Consumer credit	Dummy=1 if 'Consumer credit' owned	13.3%	0	13,245	13.5%	0	13,245	.60	
Credit card	Dummy=1 if 'Credit card' owned	26.6%	0	13,245	26.5%	0	13,245	.85	
Retirement product	Dummy=1 if 'Retirement product' owned	15.5%	0	13,245	15.5%	0	13,245	.25	
Saving product	Dummy=1 if 'Saving product' owned	8.1%	0	13,245	7.9%	0	13,245	.44	
Mortgage	Dummy=1 if 'Mortgage' owned	2.3%	0	13,245	2.3%	0	13,245	.87	
Credit default risk	Bank credit score (0=low - 1=high)	0.009	0.003	13,245	0.009	0.002	13,245	.81	
		Financials							
Cash at t=0 (August 2015)	€	4,217	1,046	13,245	4,205	1,094	13,245		.02
Share of depot owners	Dummy=1 if portfolio is owned	9.7%	0	13,245	9.5%	0	13,245	.73	
Portfolio value at t=0 (August 2015)	€	4,600	0	13,245	5,786	0	13,245		.12
Debit value at t=0 (August 2015)	€	6,955	1,336	13,245	7,237	1,438	13,245		.01
Credit value at t=0 (August 2015)	€	3,716	0	13,245	4,131	0	13,245		.51

Appendix C reports summary statistics on customer demographics, bank relationship variables and financial balances of matched treatment and control group customers who enrolled between September 1st 2015 and February 29th 2016. The columns 'Natural field experiment treatment group' and 'Natural field experiment control group' show means, median values and quantity of observations for each group. Next, we report p-values of a univariate t-test on difference of means or p-values of a univariate Mann-Whitney test if normal distribution of variable was not given, since the Mann-Whitney test is a non-parametric test and does not require a normally distributed sample. Customer demographics include information on the proportion of male customers (*Gender*), customers' age (*Age),* and respective distribution between age groups (*Age 0-15, Age 16-25, Age 26-40, Age, 41-50, Age 51-65, Age 65 plus*). *Joint account* identifies share of accounts in each group that are owned by more than one person. Distribution between the groups of marital status is reported in the variables *Single, Civil Union, Married, Separated, Divorced, Widowed* based upon customers' reported status. If the status was not provided, *No marriage reported* was set to 1. *Employee, house wife, retiree, unemployed, public employee,* and *industrial employee* report customers' employment status. *Self-employed* includes customers who work as executives or owner of a firm, while *student* includes (high school) pupils, regular students and pupils of technical apprenticeships. *No job reported* identifies customers who did not provide a job information. We use customers' registration address' first zip code number to identify their region of living (*Zip code region 0-9).*We report the number of years, a customer was with the bank (*length of relationship)* and the *intensity of relationship*, measured as the number of branch visits within the last 12 months. We report whether a customer owns at least one product from a specific product category (*Saving plan, Saving product, Retirement product, Credit card, Consumer credit, Mortgage, Portfolio owned).* The bank's internal risk score (*credit default risk)* ranges from 0 (low) to 1 (high). We compare customers' initial balances on August 31st 2015 (t=0) for current account (C*ash at t=0)*, deposits (*Debit value at t=0*) and overall borrowings (*Credit value at t=0*). Portfolio values before Field Experiment (*Portfolio value at t=0)* are reported, too.

Appendix D: Effect of tool usage on customer financials for users with salary alike inflows prior activation winsorized at top and bottom 5%

Dependent variable	Monthly wealth balance at the bank		Monthly debit balance		Monthly savings product balance, excl. current account	
	(1)	(2)	(3)	(4)	(5)	(6)
Interaction dummy $T_i t_j$	287.4** 0.04	70.3 0.31	346.8*** 0.00	219.1*** 0.00	91.6 0.20	74.3* 0.07
Dummy treatment		-5.3 0.90		-23.0 0.81		-36.8 0.15
Dummy monthly usage		-4.8 0.95		-56.8 0.59		-37.4 0.39
Dummy male		101.1* 0.05		667.0*** 0.00		36.6 0.24
Age		4.8 0.12		32.0*** 0.00		2.9 0.11
Dummy self-employed		3.6 0.99		-2859.5** 0.04		10.4 0.97
Dummy student		-129.6* 0.05		-307.0** 0.01		-24.5 0.55
Dummy housewife		-80.0 0.70		-814.4** 0.02		129.6 0.30
Dummy retiree		-143.6 0.40		-689.5* 0.05		-65.4 0.53
Dummy industr. worker		-351.0*** 0.00		-1886.7*** 0.00		-98.6** 0.03
Dummy unemployed		-439.7*** 0.00		-2155.9*** 0.00		-46.6 0.42
Years with the bank		6.0 0.12		36.5*** 0.00		0.5 0.83
Number of visits p.a.		-31.8 0.12		-46.2 0.32		8.9 0.45
Dependent financial variable at t=0 prior natural field experiment		0.9*** 0.00		0.3*** 0.00		0.9*** 0.00
Portfolio usage		329.8** 0.01				
Saving plan		266.6*** 0.00		747.9*** 0.00		334.7*** 0.00
Saving product		1162.4*** 0.00		4256.4*** 0.00		961.6*** 0.00
Retirement product		-153.8* 0.05		221.3 0.11		-84.3* 0.09
Consumer credit		-1931.0*** 0.00				
Credit card		420.3*** 0.00				
Mortgage		-1610.8*** 0.00				

Appendix D continued

Dependent variable	Monthly wealth balance at the bank		Monthly debit balance		Monthly savings product balance, excl. current account	
	(1)	(2)	(3)	(4)	(5)	(6)
Time dummy September		-46.5**		-33.1		-7.1
		0.04		*0.13*		*0.60*
Time dummy October		77.7**		76.8***		1.9
		0.01		*0.01*		*0.92*
Time dummy November		349.7***		338.7***		65.5***
		0.00		*0.00*		*0.00*
Time dummy December		309.2***		293.3***		104.8***
		0.00		*0.00*		*0.00*
Time dummy January		351.9***		340.4***		108.8***
		0.00		*0.00*		*0.00*
Time dummy February		298.3***		309.3***		135.7***
		0.00		*0.00*		*0.00*
Time dummy March		291.3***		320.9***		159.7***
		0.00		*0.00*		*0.00*
Constant	3514.6***	141.2	6050.2	760.8***	2480.0	-109.2
	0.00	*0.24*	*0.0***0*	*0.00*	*0.00****	*0.14*
Number of observations (months)	116.320	116.320	116.320	116.320	116.320	116.320
R-squared	0.0001	0.8703	0.0002	0.5861	0.0000	0.8413
P-value Kolmogorov –Smirnov test		*0.00****		*0.00****		*0.00****

Appendix D *reports cluster robust DiD OLS estimates of the coefficients related to a change in monthly balances of: total wealth, which is the sum of debit less credit balance (models 1&2*), *debit balance (models 3 & 4) and pure savings product balance, i.e. monthly debit balance less any positive current account balance (models 5 & 6). We only consider customers with salary (wage, governmental support and pensions) inflows prior to tool activation and their respective control group matches. Following (Osborne and Waters 2002), we winsorize data at the 5% and 95% percentile to remove effects from outliers in the smaller sample size. Within this table we focus on the variable* Interaction dummy *that is equal to one if a customer from the treatment group had the tool activated in a given month. Additionally, we control for multiple other independent variables: a dummy that indicates a customer being in the treatment group (*Dummy treatment*), a dummy set to one for treatment and control group, if the given month was in the post-treatment period (*Dummy monthly usage), *a dummy indicating men (*Dummy male)*, dummies indicating the reported job (*Dummy self-employed, Dummy student, Dummy housewife, Dummy retiree, Dummy industr. worker, Dummy unemployed*) the number of years a customer has been with the bank (*years with the bank)¸*the number of branch visits within the last 12 months* (Number of visits p.a.*), the balance of the respective dependent variable prior to the Natural Field experiment at t=0 (*Dependent financial variable at t=0 prior natural field experiment)*, dummies that are set to one, if a product of a specific category is owned (*Portfolio usage, Saving plan, Saving product, Retirement product, Consumer credit, Credit card, Mortgage*), time fixed-effect dummies that are set to one for each month of the observation but August 2015, ranging from September 2015 – March 2016 (*Time dummy September, Time dummy October, Time dummy November, Time dummy December, Time dummy January, Time dummy February, Time dummy March). P-values are reported below coefficients. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level. R^2 values and observations in the regression are reported. *In addition, we report P-values of a univariate Kolmogorov –Smirnov equality-of-distributions test (Smirnov 1933; Kolmogorov 1933), which tests equality of respective financial balance based on interaction dummy being set to one or zero.*

Appendix E: Current account inflows and outflows by main category one month prior and one month post money management tool activation for customers enrolling between Nov 1st 2015 and Jan 31st 2016

Spending per category, in €	Month prior tool activation (t-1)			Month post tool activation (t+1)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
				Inflows						
All inflows	4.494,04	2.333,44	7.081	4.885,72	2.311,48	7.081	.15	.41	.11	391,69
Wage and salary income	3.545,90	1.902,82	7.081	3.893,56	1.880,90	7.081	.18	.62	.14	347,66
Cost of living related inflows	14,08	0,00	7.081	11,16	0,00	7.081	.51	.25	.18	-2,92
Rental income	23,35	0,00	7.081	31,74	0,00	7.081	.21	.00	.08	8,38*
Leisure and travel related inflows	15,35	0,00	7.081	20,92	0,00	7.081	.30	.64	.09	5,56
Mobility related inflows	11,14	0,00	7.081	14,12	0,00	7.081	.64	.50	.49	2,98
Medical related inflows	11,11	0,00	7.081	7,61	0,00	7.081	.30	.44	.23	-3,50
Children related income	42,35	0,00	7.081	4,26	0,00	7.081	.00	.00	.00	-38,10***
Education related inflows	23,08	0,00	7.081	26,61	0,00	7.081	.79	.03	.74	3,53
Saving & investment income	176,29	0,00	7.081	185,61	0,00	7.081	.81	.32	.65	9,32
Insurance inflows	174,16	0,00	7.081	240,60	0,00	7.081	.00	.00	.00	66,43***
Credit related inflows	19,81	0,00	7.081	40,10	0,00	7.081	.18	.77	.18	20,29
Other inflows (incl. cash)	437,40	0,00	7.081	409,46	0,00	7.081	.54	.11	.36	-27,95
				Outflows						
All outflows	-4.226,22	-2.270,18	7.081	-4.973,37	-2.358,72	7.081	.00	.00	.00	-747,15***
Non categorized outflows	-1.630,36	-378,56	7.081	-1.920,04	-410,00	7.081	.08	.00	.05	-289,68***
Cost of living	-284,34	-173,46	7.081	-263,16	169,15	7.081	.03	.82	.00	21,18
Residential expenses	-427,05	-211,05	7.081	-427,57	-242,00	7.081	.98	.00	.95	-0,52
Leisure and travel expenses	-82,18	-2,99	7.081	-75,20	-7,00	7.081	.42	.35	.39	6,98
Mobility expenses	-85,00	-12,80	7.081	-101,70	-16,20	7.081	.23	.69	.19	-16,70
Medical expenses	-22,68	0,00	7.081	-30,43	0,00	7.081	.14	.00	.13	-7,75
Children related outflows	-8,85	0,00	7.081	-8,06	0,00	7.081	.49	.08	.24	0,79
Education and work costs	-20,49	0,00	7.081	-26,14	0,00	7.081	.01	.00	.00	-5,65***
Saving & investment outflows	-178,66	0,00	7.081	-516,35	0,00	7.081	.03	.00	.03	-337,69***
Insurance expenses	-230,10	-49,78	7.081	-295,67	-77,18	7.081	.00	.00	.00	-65,57***
Credit down payments	-170,68	0,00	7.081	-196,13	0,00	7.081	.14	.43	.09	-25,45
Other outflows (incl. cash)	-1.085,82	-611,13	7.081	-1.112,91	-583,76	7.081	.51	.23	.43	-27,08

Appendix E reports sum of monthly income and spending per money management tool category for customers who enrolled between November 1st 2015 and January 31st 2016. The columns '*Month prior tool activation (t-1)*' and '*Month post tool activation (t+1)*' show mean and median values per category. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in in formula 3.

Appendix F: Current account inflows and outflows by main category one month prior/after money management tool activation for customers with salary inflows prior to tool activation

Spending per category, in €	Month prior tool activation (t-1)			Month post tool activation (t+1)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
				Inflows						
All inflows	4.363,85	2.566,60	6.937	4.588,53	2.527,29	6.937	0.29	0.76	0.21	224,68
Wage and salary inflows	3.697,05	2.229,21	6.937	3.833,38	2.168,20	6.937	0.50	0.15	0.43	136,33
Inflows from food, beverage	6,39	0,00	6.937	6,80	0,00	6.937	0.80	0.21	0.74	0,41
Rental income	14,62	0,00	6.937	30,83	0,00	6.937	0.04	0.00	0.04	16,21***
Leisure and travel inflows	7,88	0,00	6.937	9,89	0,00	6.937	0.36	0.28	0.23	2,01
Mobility related inflows	5,50	0,00	6.937	2,05	0,00	6.937	0.14	0.18	0.13	-3,45
Health related inflows	7,36	0,00	6.937	6,07	0,00	6.937	0.55	0.74	0.44	-1,29
Children related inflows	26,39	0,00	6.937	3,25	0,00	6.937	0.00	0.00	0.00	-23,15***
Education related inflows	10,23	0,00	6.937	18,05	0,00	6.937	0.39	0.05	0.39	7,83
Savings & investment inflows	140,98	0,00	6.937	166,39	0,00	6.937	0.35	0.09	0.27	25,40
Insurance inflows	142,70	0,00	6.937	198,31	0,00	6.937	0.00	0.00	0.00	55,61***
Credit related inflows	14,46	0,00	6.937	36,50	0,00	6.937	0.12	0.93	0.12	22,04
Other inflows (incl. cash)	290,30	0,00	6.937	277,02	0,00	6.937	0.73	0.16	0.67	-13,28
				Outflows						
All outflows	-4.120,09	-2.464,35	6.937	-4.675,89	-2.557,65	6.937	.00	.00	.00	-555,80***
Non categorized outflows	-1.532,92	-423,98	6.937	-1.842,44	-474,48	6.937	.06	.00	.04	-309,52***
Cost of living	-282,93	-193,64	6.937	-280,76	-187,39	6.937	.87	.14	.86	2,18
Residential expenses	-424,92	-269,35	6.937	-444,43	-300,00	6.937	.34	.01	.04	-19,51**
Leisure and travel expenses	-85,13	-12,38	6.937	-78,98	-13,00	6.937	.45	.79	.41	6,14
Mobility expenses	-83,55	-27,85	6.937	-95,40	-29,86	6.937	.35	.23	.35	-11,85
Medical expenses	-25,83	0,00	6.937	-35,16	0,00	6.937	.10	.00	.92	-9,33
Children related outflows	-9,96	0,00	6.937	-8,63	0,00	6.937	.42	.09	.1	1,34
Education and work costs	-19,89	0,00	6.937	-26,37	0,00	6.937	.00	.00	.00	-6,48***
Saving & investment outflows	-165,03	0,00	6.937	-294,08	0,00	6.937	.00	.05	.00	-129,05**
Insurance expenses	-259,89	-79,90	6.937	-253,88	-82,50	6.937	.6	.04	.54	6,01
Credit down payments	-186,13	0,00	6.937	-194,64	0,00	6.937	.64	.35	.62	-8,51
Other outflows (incl. cash)	-1.043,92	-643,62	6.937	-1.121,12	-644,42	6.937	.04	.67	.02	-77,20

Appendix F reports sum of monthly income and spending per money management tool category for customers who activated the money management tool between November 1st 2015 and February 29th 2016 and had a salary inflow prior tool activation. The columns '*Month prior tool activation (t-1)*' and '*Month post tool activation (t+1)*' show mean and median values per category. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in in formula 3.

Appendix G: Current account inflows and outflows by main category one month post and two months post money management tool activation for customers, enrolling between Nov 1st 2015 and Jan 31st 2016

Spending per category, in €	Month prior tool activation (t+1)			Month post tool activation (t+2)			t-test	Mann-Whitney test	Cluster robust OLS	Mean-difference
Data variable	Mean (A)	Median	N	Mean (B)	Median	N	P-Value	P-Value	P-Value	(B)-(A)
Inflows										
All inflows	4.885,72	2.311,48	7.081	4.817,85	2.307,88	7.081	.27	.56	.22	-67,88
Wage and salary income	3.893,56	1.880,90	7.081	3.837,25	1.867,92	7.081	.30	.94	.26	-56,31
Cost of living related inflows	11,16	0,00	7.081	12,01	0,00	7.081	.64	.04	.37	0,85
Rental income	31,74	0,00	7.081	47,20	0,00	7.081	.08	.00	.05	15,46***
Leisure and travel related inflows	20,92	0,00	7.081	21,27	0,00	7.081	.53	.67	.51	0,35
Mobility related inflows	14,12	0,00	7.081	15,91	0,00	7.081	.50	.84	.32	1,79
Medical related inflows	7,61	0,00	7.081	10,00	0,00	7.081	.75	.69	.61	2,38
Children related income	4,26	0,00	7.081	4,96	0,00	7.081	.00	.00	.00	0,70***
Education related inflows	26,61	0,00	7.081	20,55	0,00	7.081	.83	.09	.42	-6,06
Saving & investment income	185,61	0,00	7.081	177,16	0,00	7.081	.98	.05	.97	-8,45
Insurance inflows	240,60	0,00	7.081	249,92	0,00	7.081	.00	.00	.00	9,32***
Credit related inflows	40,10	0,00	7.081	27,34	0,00	7.081	.41	.24	.29	-12,75
Other inflows (incl. cash)	409,46	0,00	7.081	394,28	0,00	7.081	.32	.06	.15	-15,17
Outflows										
All outflows	-4.973,37	-2.358,72	7.081	-4.542,26	-2.315,26	7.081	.11	.45	.07	431,12
Non categorized outflows	-1.920,04	-410,00	7.081	-1.789,25	-415,57	7.081	.44	.86	.39	130,79
Cost of living	-263,16	169,15	7.081	-251,34	-163,45	7.081	.15	.02	.03	11,82**
Residential expenses	-427,57	-242,00	7.081	-443,06	-250,00	7.081	.34	.49	.19	-15,49
Leisure and travel expenses	-75,20	-7,00	7.081	-112,64	-7,49	7.081	.29	.85	.29	-37,44
Mobility expenses	-101,70	-16,20	7.081	-95,87	-16,55	7.081	.71	.79	.69	5,84
Medical expenses	-30,43	0,00	7.081	-30,15	0,00	7.081	.96	.56	.96	0,29
Children related outflows	-8,06	0,00	7.081	-8,62	0,00	7.081	.70	.29	.466	-0,56
Education and work costs	-26,14	0,00	7.081	-32,85	0,00	7.081	.01	.00	.00	-6,72***
Saving & investment outflows	-516,35	0,00	7.081	-168,23	0,00	7.081	.03	.28	.03	348,12
Insurance expenses	-295,67	-77,18	7.081	-251,85	-66,15	7.081	.00	.00	.00	43,82***
Credit down payments	-196,13	0,00	7.081	-260,88	0,00	7.081	.29	.20	.28	-64,75
Other outflows (incl. cash)	-1.112,91	-583,76	7.081	-1.097,05	-585,14	7.081	.72	.91	.65	15,86

Appendix F reports sum of monthly income and spending per money management tool category for customers who activated the money management tool between November 1st 2015 and January 31st 2016. The columns '*Month prior tool activation (t-1)*' and '*Month post tool activation (t+2)*' show mean and median values per category the month prior and the second month after FP activation. Next, we report P-values of the within subject event study of a univariate t-test, a non-parametric Mann-Whitney test and a cluster robust OLS regression. As transactions per category are not normally distributed, we report t-test results only for completion. We report mean differences in the last column. *** indicates significance at the 1% level, ** significance at the 5% and * significance at the 10% level of the Mann-Whitney test and the cluster robust OLS regression. The OLS regression is of the form stated in in formula 3.

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