Contents

Chapter 1

Introduction

The overall aim of this thesis is to use transaction-level data from a financial aggregator app, insights from behavioural science, and methods from econometrics and machine learning to contribute to a better understanding of the determinants of how individuals spend their money and save for the short-term. This introductory chapter first discusses the context within which this research takes place, and then introduces the main chapters of the thesis.

1.1 Context

1.1.1 Financial wellbeing

Financial wellbeing is a state in which a person can make ends meet in the present, can feel comfortable about their financial future, can feel comfortable about money, and has the financial freedom to make choices that allow for the enjoyment of life. This includes having control over ones day-to-day and month-to-month finances, not having to borrow to meet ongoing obligations, being free of debt or being in control of it, having the capacity to meet unexpected expenses, and – for a working-age individual – being on track to build enough savings for retirement.[1]

Financial wellbeing is important because a lack of it can have severe consequences both in the short-term and in the long-term. In the short-term, low

[1]The US Consumer Financial Protection Bureau defines financial wellbeing as “a state of being wherein a person can fully meet current and ongoing financial obligations, can feel secure in their financial future, and is able to make choices that allow enjoyment of life” (CFPB 2015). The UK’s Money and Pension service defines current financial wellbeing as “being able to pay the bills and feel comfortable about money” and longer-term financial security as “having the savings to deal with the expected, the unexpected and the longer-term; or having some form of loss protection such as home contents or life insurance” (MPS 2018). Both organisations also differentiate some aspects of financial wellbeing depending on whether an individual is in their working or retirement age. Throughout, this discussion, as well as in the analysis in the following chapters, I focus on working age individuals.

financial wellbeing means a constant struggle to make ends meet, being overwhelmed by debt, having circumstances dictate ones of and approach to money, a higher likelihood of experiencing material hardship – which (CFPB 2017) defines as running out or worrying about running out of food, not being able to afford medical treatment or a place to live, or have utilities turned off – and the need to cut back on essentials for ones children.[2] All of these experiences can cause a decline in physical and mental health, a loss of productivity, and an overall deterioration in the quality of life.

In the long-term, the danger is that the situation is not only self-sustaining but leads to a vicious circle that becomes increasingly hard to escape. This can happen purely because having to borrow for regular expenses like food and bills – as, the Money and Pension service estimates, about 9 million adults in the UK do (MPS 2018) – can lead to a situation where an increasing amount has to be spent on servicing debt and thus increases monthly expenses and the borrowed amounts required to cover them. In addition, however, this could happen because of increasingly impaired decision making. A literature on mental scarcity documents that our minds tend to focus on what is scarce and neglect what is not, concentrating our mental resources where they are most needed but reducing cognitive bandwidth in other domains, which can lead to poorer decision making (Shah et al. 2012, Mullainathan and Shafir 2013, Haushofer and Fehr 2014). For instance, Mani et al. (2013) find that low-income shoppers in New Jersey perform worse on cognitive tasks when first promoted to think about their financial situation while the same prompts had no effect for wealthier shoppers, and sugar cane farmers in India perform worse on similar cognitive tasks shortly before the annual harvest (when money is scarce) than shortly thereafter (when money is plentiful). There is also evidence that scarcity might lower productivity in the present: Kaur et al. (2021) randomise the timing of wage payments to low-income piece-rate manufacturing workers and find that workers that receive their wages early and are thus no longer liquidity constrained make fewer mistakes and increase their output by 7 percent. Hence, if the anxiety caused by having little money to cover current expenses lowers individuals' productivity in the present and makes it harder to engage in rational planning for the future – how to reduce spending, how to build skills that would help find a higher-paying job, how to transition to a healthier lifestyle that would help them feel and perform better physically and mentally – then low financial wellbeing in the present might beget low financial wellbeing in the future.

The determinants of financial wellbeing are a combination of circumstantial

[2] For more detailed descriptions about the consequences of financial hardship, see CFPB (2017), MPS (2018), and Step Change (2017).

and external factors as well as the capabilities, believes, and behaviours of the individual. MPS (2018) provides a useful categorisation that sees financial wellbeing as a function of four broad factors: external factors that include economic conditions, demographics, and a person's social environment; enablers that include financial confidence and numeracy, a sense of control, ones spending and savings mindset, and ones engagement with money, advice, and technology; day-to-day behaviours like managing the use of credit, avoiding to borrow for everyday spends, active saving, keeping track of and making adjustments to ones spending, and shopping around; and, finally, planning ahead behaviours like building financial resilience through saving and planning for retirement.[3]

While no one factor is deterministic for financial wellbeing, research from the US (CFPB 2017) and the UK (MPS 2018) agrees that, as expected, external economic factors such as access to education and higher paying jobs are important. In the UK, for instance, individuals with an annual income of £20,000 or below account for 41 percent of the working age population but for 69 percent of those with less than £100 of savings. Similarly, 50 percent of people who borrow to cover everyday expenses earn less than £17,000. So, clearly, a search for and support of effective economic and social policy measures should be an important part of any effort to improve societal financial wellbeing. But the same research also shows that higher incomes are not sufficient. In the UK, 18 percent of individuals with less than £100 in savings have a household income of £30,000 or higher, and 20 percent of those who borrow to cover everyday expenses have an income of £50,000 or higher. In the US, too, there is large variation in the characteristics of individuals at each level of financial wellbeing; the financial wellbeing of the top quarter of people with a high-school degree, for instance, is higher than that of the bottom half of those with graduate degrees.

In both countries, research shows that the level of savings is a key contributor to financial wellbeing. In the US, it is the one factor that discriminates between different levels of financial wellbeing better than any other examined factor (CFPB 2017). In the UK, it is, together with behaviour towards credit, the strongest predictor of financial wellbeing (MPS 2018). In fact, research by a UK charity suggests that having £1,000 in liquid savings could reduce the probability of being in debt by almost half. In particular, having a habit of saving regularly – even more so than the amounts saved – has been found to be a key determinant. Other factors that are positively associated with higher financial wellbeing are confidence in ones ability to achieve ones financial goals, not using debt to cover everyday expenses, paying ones bills on time, staying within ones

[3] The US Consumer Financial Protection Bureau uses a similar classification in its definition of financial wellbeing (CFPB 2015).

budget and spending plan, paying credit card balances in full, and checking bank statements for errors.[4]

But many people struggle with these behaviours. For instance, in the UK, 21 percent of the working-age population (10.7 million adults) report to rarely or never save, and 22 percent of the population have less than £100 in savings, with those holding that amount in a formal savings account being even lower (MPS 2018). Unsurprisingly, then, one in four adults could not pay an unexpected bill of £300 from their own money (Phillips et al. 2021). In the US, the situation is similar: 30 percent of adults report that they would be unable to cover a bill of $400 in cash or its equivalents (Governors of the Federal Reserve System 2022), and, according to a 2013 survey, liquid net worth for the median household with a head aged 41-51 is only $813, whereas at the 25th percentile it is -$1,885 (Beshears, Choi, Laibson, and Madrian 2018).[5]

This is problematic because many households do face unexpected financial shocks over the course of a year. Also, many households experience high income volatility: in the US between 2013 and 2018, the median month-to-month change in household income was 36 percent, with low-income households experiencing more frequent and larger income dips (Chase 2019). The same research finds that while families need roughly six weeks of take-home income in liquid assets to weather a simultaneous income dip and expenditure shock, 65 percent of households lack such a buffer. In line with these findings, Roll and Despard (2020) find that during the coronavirus pandemic, households with liquid asses of above $2,000 had significantly lower risk to experience financial distress (indicators like skipping essential bills, being behind on credit card debt, being in overdraft) than households with lower savings.

Managing debt is similarly challenging for many. 9 million people in the UK also borrow to cover expenses for food and bills (MPS 2018), and many struggle to stay on top of their credit card debt: 2 million cards were in arrears or default, another 2 million carried persistent debt, and for another 1.6 million cards, owners were persistently making minimum payments only. Altogether, the study found that 5 million accounts (9 percent of the total) that were active in January 2015 would, under their current repayment pattern and without further borrowing, take 10 years to repay their balance (FCA 2016). In addition to holding high and persistent balances, a large body of research also indicates that individuals make other mistakes in debt management, especially in dealing with credit cards: they choose suboptimal credit card contracts (Agarwal, Chomsisengphet, Liu, et al.

[4]For details on contributors to financial wellbeing see (CFPB 2017) for the US and MPS (2018) for the UK.

[5]Liquid net worth includes all assets (except pension wealth, retirement savings, homes, and durable assets) net of all debt (except student loans and collateralised debt).

2015), sometimes because they are overly susceptible to temporarily low teaser rates (Shui and Ausubel 2004, Ausubel 1991); they borrow on payday loans before while being far from having exhausted their credit card limits (Agarwal, Skiba, et al. 2009), their repayment amount is overly influenced by stated minimum payments (Sakaguchi et al. 2022), they pay down debt across different cards proportionally to outstanding balances instead of prioritising high-interest cards (Gathergood, Mahoney, et al. 2019), and they sometimes hold credit card debt and liquid assets at the same time (Gross and Souleles 2002, Gathergood and Olafsson 2020).[6]

1.1.2 Behavioural science

Behavioural science can help address these challenges by understanding the factors that determine financial behaviour and by designing and testing possible solutions. The main factors that have been found to influence financial decision making are: cognitive limitations and financial literacy (Agarwal, Driscoll, et al. 2009, Agarwal and Mazumder 2013, Korniotis and Kumar 2011, Agarwal, Amromin, et al. 2010, Fernandes et al. 2014, Jørring 2020); time-preferences and self-control (Frederick et al. 2002, Read et al. 2018, Ericson and Laibson 2019, Cohen et al. 2020); attitude towards money and spending (Rick, Cryder, et al. 2008, Rick, Small, et al. 2011); ones perceived locus of control (Perry and Morris 2005), degree of optimism (Puri and D. T. Robinson 2007), ability to frame decisions broadly rather than narrowly (Kumar and S. S. Lim 2008), and propensity to gamble (Kumar 2009); ones social network (Bailey, Cao, et al. 2018, Kuchler and Stroebel 2021); the degree of ones financial planning (Ameriks et al. 2003); and habits (J. Blumenstock, Callen, et al. 2018, Schaner 2018, De Mel et al. 2013).[7]

Researchers have also developed and tested a large number of approaches aimed to help people make better decisions. One main area of research here aims to address limited self-control – the difficulty most of us face at least occasionally to act, moment-by-moment, in our own best interest and according to our own goals. I briefly discuss four such approaches that have the potential to help people make the financial choices they themselves would like to make. A complete review of that literature is provided by Duckworth et al. (2018).

One extensively studied approach are commitment devices, whereby an individual restricts their future choice set in order to avoid choosing a self-defeating

[6] See Agarwal, Chomsisengphet, and C. Lim (2017) for a more complete review of a large body of research documenting consumer choice inefficiencies and suboptimal financial behaviour.

[7] For two thorough reviews, see Agarwal, Chomsisengphet, and C. Lim (2017) and Greenberg and Hershfield (2019).

action. While not everybody makes use of such devices when offered the opportunity (Bryan et al. 2010), and while they do not work in all contexts (Laibson 2015, C. D. Robinson et al. 2018), they have been found to help individuals increase their savings rates (Ashraf et al. 2006), quit smoking (Giné et al. 2010), make healthier food choices (Schwartz et al. 2014), and exercise more regularly (Royer et al. 2015).

Another approach are implementation intentions, a particular type of planning for the achievement of ones goals that involves "if-then" intentions, such as "if I get paid, then I transfer 10 percent of it into my savings account" (P. M. Gollwitzer and Sheeran 2006, Rogers, Milkman, et al. 2015). Such intentions have been found to support perseverance in pursuing ones goals (Oettingen and P. Gollwitzer 2010) and to increase overall goal attainment across different age groups, life domains, and types of obstacles (P. M. Gollwitzer and Sheeran 2006).

A third intervention that has the potential to alter financial behaviour is social norms messaging, whereby people are informed about how their own behaviour compares with that of a relevant peer group. Such information can be especially useful for domains where such information is usually not available, as is the case with spending and saving, and has been successful inducing high energy use households to lower their energy use without inducing low-use households to increase theirs (Schultz et al. 2007, Allcott 2011, Allcott and Rogers 2014, Brandon et al. 2017). However, the information can also backfire and has been found to lower participation in pension savings plans (Beshears, Choi, Laibson, Madrian, and Milkman 2015) and completion rates of an online course (Rogers and Feller 2016), making it important to test messages before deploying them on a large scale and to avoid unintended consequences.

Finally, changing default options has been found to be a powerful tool for behaviour change. Defaults are consequential because people often stick with the status quo Samuelson and Zeckhauser (1988), and because they tend to interpret defaults as a recommendation (McKenzie, Liersch, and Finkelstein 2006), implicitly view it as a reference point moving away from which would feel costly Johnson and Goldstein (2003) and Kahneman and Tversky (1979), and because even if they resolve make a different choice, they often procrastinate Carroll et al. (2009) and Ericson (2017). Default options have been applied across range of areas and have, for instance, been found to increase retirement savings contributions (Madrian and Shea 2001, Beshears, Choi, Laibson, and Madrian 2009) and organ donations (Johnson and Goldstein 2003, Gimbel et al. 2003, Abadie and Gay 2006).

These approaches, together with many others, have the potential to make it easier for individuals to manage their money and to spend and save in line with their own goals. To realise that potential, however, they have to be tested on a large scale and at low cost to gather reliable results and to have the ability to tweak and refine them. Furthermore, solutions that are found to work have to be deployed on a large scale to have a meaningful impact. The advent of online and mobile banking and the large amount of data they create enable researchers and financial institutions to do just that.

1.1.3 FinTech

The availability of large amounts of granular data about human behaviour, together with ongoing progress in the development of machine-learning algorithms elicit information from them, and the increase in computer power that allows for the storage and processing of the data and the deployment of these algorithms, offers enormous potential for better understanding human behaviour (Jaffe 2014, Buyalskaya et al. 2021) and for building applications that help people live in line with their goals.

Platforms like Facebook provide the opportunity to recruit study participants at a scale and with an ease that was not possible before (Kosinski et al. 2015), and data from its platform has been used, for instance, to predict participant personalities and life outcomes (Youyou et al. 2015), and to study the effect of social interactions on house purchasing decisions (Bailey, Cao, et al. 2018, Bailey, Dávila, et al. 2019), the spatial structure of urban networks (Bailey, Farrell, et al. 2020), the role of peer effects in product adoption (Bailey, Johnston, Kuchler, et al. 2019), the role of social networks in determining social distancing during the coronavirus pandemic (Bailey, Johnston, Koenen, et al. 2020), and the determinants of social mobility (Chetty et al. 2022a, Chetty et al. 2022b). Similarly, log and sensor data from mobile phones, another increasingly popular data source in the study of human behaviour, has been used to successfully predict personality traits (Montjoye et al. 2013, Stachl et al. 2020), predict levels of wealth (J. Blumenstock, Cadamuro, et al. 2015), improve human aid targeting (Aiken et al. 2022), and study the role of social networks for migration patterns (J. E. Blumenstock et al. 2019). Some studies also combine data from a range of sources; in one ambitious project, Chi et al. (2022) use data from satellites, mobile phone networks, topographical maps, and aggregated and de-identified connectivity data from Facebook to map levels of wealth and poverty at a 2.4km resolution for all 135 low and middle-income countries (Chi et al. 2022).

In the area of household finance, the advent of online and mobile banking is creating an every growing amount of transaction-level data and a range of FinTech apps aimed to help people manage their money. There are three ways in which such data and apps act as critical enablers for an improved understanding of financial behaviour and for the development, testing, and deployment of possible solutions that help increase financial wellbeing.

First, large-scale and granular transaction data is an invaluable resource to help researchers refine their understanding of the behavioural determinants of financial decision making because it tends to have one or many of the following attributes: it is collected automatically and thus more reliably, it provides a more complete view of an individual's financial life, it spans a longer time horizon, it covers a larger set of individuals, and the cost of collection (though not necessarily cleaning) is zero. Accordingly, such data has already been used to study a range of issues. For instance, Kuchler and Pagel (2020) show that a failure to stick to self-set debt paydown schedules is best explained by individual's present biasedness, Gelman et al. (2014) and Olafsson and Pagel (2018) show that consumer spending varies across the pay cycle, Baker (2018) and Baugh et al. (2014) study consumer spending responses in response to exogenous shocks, Carlin et al. (2019) document generational differences in financial platform use, Ganong and Noel (2019) show that consumer spending drops sharply after the predictable income drop from exhausting unemployment insurance benefits, Meyer and Pagel (2018) analyse how individuals reinvest realised capital gains and losses, and Muggleton et al. (2020) show that chaotic spending behaviour is a harbinger of financial distress.[8]

Second, the FinTech apps from which such data are often gathered allow for testing and the gradual refinement of possible solutions at high speed and relatively low cost. Furthermore, because these apps are often built to help users manage their money, they have a clear incentive to do so, something that is not true to the same extent for more traditional banks. Some work that tests the effectiveness of FinTech apps aimed to facilitate money management has already been conducted: Gargano and Rossi (2021) find that an app that allows users to set savings goals does indeed increase savings, and Levi and Benartzi (2020) and Carlin et al. (2022) find, respectively, that improved access to financial information reduces discretionary spend and non-sufficient fund fees.

But there is large potential for further work in this area. For instance, while the work of Levi and Benartzi (2020) suggests that lowering the cost of access to financial information can improve financial outcomes, little is known about what design features of mobile apps are particularly helpful. There are also features that are not currently in widespread use that could address known biases. One example is our tendency to underestimate the power of exponential growth. McKenzie and Liersch (2011) find that highlighting participants in a series of

[8]For a comprehensive review of the literature using financial transaction data, see Baker and Kueng (2022).

experiments the effects of exponential growth motivates them to save more. It would be easy for mobile apps to project accumulated future savings for different monthly savings amounts, say, and thus make the future loss from spending more money in the present more salient. Another example is mental accounting. Soman and Cheema (2011) find that earmarking part of peoples' salaries as savings increases savings rates. FinTech apps could, for instance, suggest to automatically transfer fixed amount into labelled savings pot, thus making that money less likely to be spent later. Finally, increasingly sophisticated "robo-advisers" – financial advise provided by machine-learning algorithms – has the potential to democratise personalised financial advise across an increasing number of domains, from portfolio allocation to consumption decisions to debt management (Philippon 2019, D'Acunto and Rossi 2021).

In testing and refining possible solutions, the large size of the data is critical because it allows for the identification of heterogeneous effects and allows for the appropriate customisation of solutions. Having a view of users' entire financial lives – as in the case of financial aggregator apps that allow users to add accounts from all their different financial providers – is also critical, since it allows for the identification of unintended consequences; for example, inducing credit card users to make higher automatic card repayments may increase automatic repayments but leave the total repayment amount unchanged (Guttman-Kenney et al. 2021), and auto-enrolling employees into pension schemes might increase their debt levels (Beshears, Choi, Laibson, Madrian, and Skimmyhorn 2022).

Finally, FinTech apps will make it relatively simple and cheap to make effective solutions and tools widely available to a large audience, which is critical to the goal of increasing financial wellbeing on a large scale.

All these opportunities from ever-growing data and increasingly sophisticated algorithms and powerful computers bring – like all innovations – a set of challenges. They can, for instance, compromise individual privacy and propagate social biases. Inevitably, technological progress has largely outpaced regulatory responses, and it will take time to understand all the implications of these new technologies and enshrine proper safeguards into law. In the meantime, leading researchers in the field are charting the course in thinking about how to work with these data and tools responsibly (De Montjoye et al. 2015, Kosinski et al. 2015, J. Blumenstock 2018), and private companies as well as research institutions have put in place safeguarding procedures to ensure that such best practices and current regulations are followed at the level of individual research projects.

1.2 Thesis outline

The thesis consists of three stand-alone chapters, each of which addresses a different aspect of the overall aim of the thesis – to combine large-scale transaction data, insights from from behavioural science, and methods from econometrics and machine learning to study how individuals spend and save.

Chapter 2, which is joint work with Neil Stewart, introduces and tests a new method that allows researchers to elicit behaviour traits of the type used in lab and survey studies for individuals in large datasets. This work contributes to the overall thesis purpose indirectly in that it aims to augment the information contained in large datasets with additional information that opens up additional avenues of research and helps researchers fully leverage the data in their study of human behaviour.

Chapter 3 tests whether the way individuals spend their money is related to how frequently they make transfers into their emergency savings funds. The overall aim of the chapter is to test whether simple summary statistics based on spending spending profiles – the way in which individuals allocate their spending transactions across different product and merchant categories – capture information about individuals' life circumstances that are predictive of their financial behaviour. If so, such statistics could be used in financial management apps, to, for instance, provide extra and customised assistance in time of need.

Chapter 4 tests whether using Money Dashboard – the financial aggregator app that provides the data for all chapters of this thesis – is associated with a reduction in discretionary spend and an increase in emergency savings. The aim is to contribute to a better understanding of the extent to which the potentially large benefits of FinTech apps already help users achieve their financial goals and thus raise financial wellbeing.

Chapter 2

Machine-learned behaviour traits

Chapter 3

Spending entropy predicts savings behaviour

Chapter 4

Do Money Dashboard users spend more and save less?

Chapter 5

Conclusion

This thesis consists of three stand-alone chapters, each of which addresses a different aspect of my overall aim of using large-scale transaction level data, insights from behavioural science, and methods from econometrics and machine learning to study how individuals spend money and save for the short-term.

Chapter 2, which is joint work with Neil Stewart, introduces a novel approach to elicit time preferences from mass financial transaction data. Lab and field studies typically elicit time preferences by making participants choose between a smaller-sooner and a larger-later effort or payoff. The core idea of our approach is to identify a series of consumption choices that mimic this trade-off, and then exploit these choices to estimate time preferences not only for the subset of users for whom we observe the choice in the data but for all users in the data.

The three choice scenarios we identify are monthly or yearly payment for car insurance, purchasing a new mobile phone outright or paying in monthly instalments, and swapping car and home insurer frequently or infrequently. Each of these choices implicitly trades off a higher cost or effort in the present but reduced cost in the future with lower cost or effort in the present but higher-cost in the future. We identify individuals in our dataset that engage in each of these choice scenarios, and then predict their likelihood of making the patient choice based on features we extract from the data. We call that likelihood individual's propensity for patience. We then use this predictive model to predict the propensity for patience also for those users in our dataset who didn't engage in a particular choice scenario. Finally, we test whether predicted propensities from difference choice scenarios correlate positively, as we would expect if they all elicit the same underlying time preferences.

The main appeal of the approach is that, if successful, it would allow researchers to estimate time-preferences for a large set of individuals based on the smaller-sooner and larger-later payoff approach that researchers commonly use in lab experiments. More broadly, the general approach we introduce – identify scenarios that identify choices used to estimate behaviour traits, train a prediction model on individuals in the data for whom that scenario is observed, and use that model to predict the trait for all individuals in the data – could, in principle, be used for other behaviour traits, too. Large-scale observational data of the type used in this study has become available only in recent years and is increasingly used across the social sciences. Once challenge with such data is that they do not usually provide the same detailed information about behaviour traits that can be gained from observing a small set of people in a lab. Our approach has the potential to bridge that divide by allowing researchers to augment large-scale observational data with behaviour traits elicited from the data itself.

We find, however, that propensities based on different choice scenarios are uncorrelated, suggesting that in our particular application, our approach is unsuccessful at eliciting underlying preferences. There are three ways in which our work could be refined in future research. First, identifying choice scenarios is made more challenging because of imperfect tagging of transactions in the data, and because we do not have direct access to the algorithms used for tagging. Using the approach on data with more complete and reliable tagging or in collaboration with the data provider, so that anomalies in the data can be identified and handled, could eliminate that source of risk. Second, the prediction models we used could be enhanced both with additional features and by the use of more sophisticated models and further tuning. In terms of features, we have already discussed that, in our context, adding variables that more fully capture users' financial constraints might have been useful. Furthermore, we have relied on a relatively straightforward set of features, that could probably be augmented. In terms of models, we have used a number of relatively simple "off-the-shelf" models. Using more advanced models could help provide more accurate predictions. Finally, it is possible that people the way people actually make intertemporal choices is not well captured, even approximately, by the discounting models on which our elicitation approach builds. If this is true, then either eliciting time-preferences based on a different framework, or focusing on eliciting different behaviour traits might prove more successful.

Chapter 3, also join work with Neil Stewart, calculates simple summary statistics of individuals' spending profiles and tests whether differences in spending profiles are predictive of the frequency with which individuals make transactions into their savings accounts. To summarise spending profiles, we calculate the entropy of an individual's spending profile in a given period, which captures the predictability of spending transactions in said period.

We focus on spending profiles for three reasons: first, our understanding of how individuals spend their money is largely based on survey data from a relatively small number of individuals. Large-scale transaction data of the type used in this paper has become available to researchers only in recent years and has not, to the best of our knowledge, been used to explore patterns in consumer spending behaviour. Second, research suggests that spending profiles might reflect circumstances in an individual's life that are also related to their saving behaviour. Spending entropy, defined similarly as in this chapter, has been found to predict financial distress, calorie intake, and the frequency of and amount spend during supermarket visits. Finally, we think of our focus on spending profile as a proof of concept for the broader agenda of testing whether we can extract simple summary statistics from large-scale transaction data that capture relevant information about individuals' life circumstances. If successful, such information could be used in the design of financial management apps to provide timely and customised assistance to users when they need it most.

Our results show that spending entropy is predictive of the frequency of savings transactions, with an effect size similar to that of an increase in monthly income income of between £1,000 and £2,000. This holds true if we control for simple component parts of entropy, suggesting that the non-linear way in which entropy combines these components captures something about spending profiles that is of relevance. The results are also largely consistent across entropy measures calculated based on different product and merchant categories. However, they direction of the effect changes for different types of entropy that differ in the way in which we treat product or merchant categories in which an individual makes no transactions in a given period. Exploratory research suggests that the number of such zero count categories, together with the variation of counts for categories with a positive number of transactions, goes some way in explaining the outcome. But more work is necessary to more fully understand this outcome, which we leave for future research.

Chapter 4, tests whether using Money Dashboard is associated with a reduction in discretionary spending and an increase in emergency savings. I use a new estimator proposed by Callaway and Sant'Anna (2021) that corrects for recently identified problems in two-way fixed effects estimates.

I find that users reduce their discretionary spend by between £100 and £150 (11-17% of average discretionary spend) once they start using the app and sustain that reduction throughout the six-month post-signup period I consider. Looking at disaggregated measures of discretionary spend further shows that the reduction is the result of maintained month-to-month changes in behaviour rather than one-off cancellations of direct-debit transactions, that it results from reducing spending on a number of different categories of purchases rather than a single one, and that it is a result of changes along the extensive rather than the intensive margin – users reduce the number of transactions they make rather than the value of the average transaction. Interestingly, users do not seem to use these additional funds to build up emergency savings: net-inflows into savings accounts do not change after signup. I can also neither find significant increases in flows into investment and pension accounts or additional savings accounts that are not linked to the app, not additional loan repayments.

The main limitation of my approach is that I cannot isolate the effect of MDB use from possible confounding factors that let users to self-select into using the app in the first place, and that I cannot isolate the effect of individual components of the app such as information and goal-setting. However, I do find that app use is associated by a statistically and economically significantly reducuction of discretionary spend that is sustained for at least six months, and that seems to be brought about by a reduction in the number of purchases across a number of spending categories. This provides novel insights into how people that probably do have some unobserved motivation to reduce their savings actually achieve this. The additional finding that a reduction in spend is not accompanied by a commensurate increase in either short-term savings, investments, or debt-reduction suggests that people use the saved funds for a variety of different purposes.

The findings also suggest promising directions for further research. First, the substantial drop in discretionary spend associated with app use does suggest that MDB and apps like it might have a positive causal impact on financial outcomes, making it worthwhile to study their effect in more detail in ways that account for the two limitations mentioned above. Second, the finding that people may direct saved funds towards a number of different purposes can be the result of differences in funds use across or within people or a combination of the two. Within people variation in fund use could suggest the possibility that people direct additional cash-flows towards a number of different uses instead of towards those with the highest payoff, such as paying down credit-card debt or investing in government-subsidised high-interest investments. Further research establishing to what extent there is within-person variation of fund use, and whether such funds are directed towards the most effective uses would provide further useful insights into savings behaviour, and could serve as the basis for further development of financial aggregator apps to help users direct saved funds towards the most effective users.

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