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. Unsurprisingly, then, one in four adults could not pay an unexpected bill of £300 from their own money. In the US, the situation is similar, with 30 percent of adults saying they would be unable to cover a bill of $400. 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.

Beef up with additional data and refs

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. 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

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

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).[5]

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).[6]

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 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),

[5]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.

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

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, Johnston, Koenen, 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.[7]

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 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. So-

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

man 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

This thesis consists of three stand-alone chapters that all share the overall aim of combining transaction-level financial data, insights from behavioural science, and statistical methods to better understand how individuals spend and save money – with the ultimate aim of producing insights that can inform the design of tools aimed to increase financial wellbeing. A particular focus is on studying "emergency savings" – short term savings accumulated as a buffer against unexpected financial shocks – because such savings, as we have seen above, are a critical component of financial wellbeing and because, in contrast to other components like pension contributions, it is understudied. Apart from Beshears, Choi, Iwry, et al. (2020), who study design options for automated contributions to emergency saving pots, and Phillips et al. (2021), who test such a design in the UK, there is no research on how we can help individuals build such emergency savings.

Chapter 2 introduces and tests a new method that allows researchers to elicit for individuals in a large datasets behaviour traits of the type used in lab and survey studies. 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. We test our method...

Chapter 3 tests whether the way individuals spend their money is related to how frequently they make transfers into their emergency savings funds. We ...

Chapter 4 ...

- link to replication crisis - see davidthesis

- vision ahead of reality

- I use a single dataset, provided by Money Dashboard, for all three papers.
- The data presented a number of challenges.
- Handling data of this size.
- Secure storage with easy remote access (AWS).
- Consistenc and efficient preprocessing (my process).
- Open science contribution: all work available on Github, code available for preprocessing from beginning to end.

Motivation: My experience as a researcher in well-known academic and private-sector institutions has made clear to me over the years that careful, reliable, and replicable data preprocessing is undervalued in many settings.

The result are plain data errors that overturn results (Reinhard and Rogoff) and replication issues (see Ariely controversies). Given my experience, I'd think that all we know is the tip of the iceberg.

In the vast majority of empirical research projects there is no good reason to not make the code public, even when the data is proprietary. And yet, for the vast majority of papers, there is no code available to replicate findings and check precise implementation details, which often matter but are not described in papers.

All of this harms science - the quality of it and the trust in it.

I have dedicated a lot of time during my PhD to ensure that I can rectify at least some of those issues.

The code for all my projects is available online and includes scripts that can be used to easily run the entire analysis.

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

5.1 Chapter summaries

This thesis consists of three independent research studies on ...

In the first part of this conclusion, I will summarise the three chapters, before discussing challenges...

There is a lot more work to be done in characterising spending profiles. From entropy paper: There are a number of alternative ways to characterise spend profiles. We could calculate profiles based on the distribution of transaction values rather than counts. We could also calculate profiles based on inter-temporal rather than intra-temporal distributions, focusing on consistency of purchasing behaviour over time rather than on predictability at any given time (Krumme et al. 2013). Further, we could focus on time-based rather than category-based measures, focusing, for instance, on whether purchases of the same type tend to occur on the same day of the week (Guidotti et al. 2015). Finally, one could also create composite measures based on principal component analysis, an approach used in Eagle et al. (2010). We leave these extensions for future research.

5.2 Contribution

- Generally understudied

Exception: - beshears2022borrowin **philipps2021supporting** - Automatic payroll deduction seems to be valued by employees and has helped people from the squeezed and struggling segments

5.3 Limitations and directions for further research

- Financial product design agarwal2017shapes - Regulation agarwal2017shapes - chater and loewenstein

- baker2022household

- Sample representativeness

- Can often only use small fraction of users for study because of incomplete data for many. One reason: mps2018building points out that many people use budgeting tools to achieve short term goals. Hence, no intention of long-term use.

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