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The Effect of Payment Methods on Personal Finance Management

by

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of

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Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. It has been composed by myself and has not been submitted in any previous application for any degree. All work presented was carried out in collaboration with co-authors as follows:

Chapter 3 is co-authored with Neil Stewart (Warwick Business School, University of Warwick) and Andrea Isoni (Warwick Business School, University of Warwick). Data for Study 1 was collected by myself and several research assistants. Data for Study 2 was collected by myself, the study itself was conducted online and coded up by myself and Tyson Hayes (Warwick Business School, University of Warwick). The concept of the paper was developed by myself, with input of the co-authors. I collated and analysed the data. I wrote the manuscript with edits by my co-authors. The paper has received a revise and resubmit from the *Journal of Behavioral Decision Making*.

Chapter 4 is co-authored with Neil Stewart and Andrea Isoni. Data was provided by a Financial Aggregator App to Neil Stewart. The concept of the paper was developed by myself, with input of the co-authors. I collated and analysed the data. I wrote the manuscript with edits by the co-authors.

Chapter 5 is co-authored with Neil Stewart and Andrea Isoni. Data was provided by a Financial Aggregator App to Neil Stewart. I developed the concept of the paper, based on the previous chapter, and collated and analysed the data. I wrote the manuscript with edits by the co-authors.

Chapter 6 is co-authored with Neil Stewart and Andrea Isoni. All authors developed the concept of the paper together. Data for Study 1 was provided by a Financial Aggregator App to Neil Stewart and was analysed by me. Data for Study 2 were collected by me, but the methodology for the online experiment was coded by me, Neil Stewart and Tyson Hayes. I analysed the data and wrote the paper with edits from the co-authors.

Abstract

This thesis consists of four independent research studies in the field of behavioural science. Each study is concerned with studying the effect of payment methods on various aspects of personal finance management, such as spending and spending recall.

Chapter 3 studies the effect of contactless on expenditure recall conducting two studies. Study 1 is an observational study, using a survey methodology to approach the effect of contactless payment methods on expenditure recall, finding that the expenditure recall associated with contactless is significantly worse than that associated with cash, but a bit better than that associated with PIN-verified payment methods. Study 2 is a partly online study, randomly allocating participants to one payment method, measuring a variety of individual factors, also using a survey methodology, finding that contactless significantly reduces expenditure recall accuracy compared to cash, as well as compared to PIN-verification.

Chapter 4 studies the effects of the onset of contactless usage on personal finance management, measured in spending, overdraft fees, cash usage, savings and credit card debt. Applying an event study to the transaction data provided by a Financial Aggregator App, we find that contactless usage significantly increases spending frequency and amount, cash usage and savings on the contactless enabled account, and that these effects persist on the contactless user level.

Chapter 5 studies the effects of the onset of mobile payment usage on personal finance management, measured in spending, overdraft fees, cash usage, savings and credit card debt. Applying an event study to the transaction data provided by a Financial Aggregator App, we find that mobile payments significantly increase spending frequency and amount, cash usage and savings, as well as significantly reduce the likelihood of obtaining an overdraft fee, on the mobile payment enabled account. Most of these effects, apart from the significant increase in spending amount, persist on the mobile payment user level as well.

Chapter 6 introduces a new perspective on the behavioural outcomes associated with

different payment methods, arguing that it is the change in the underlying spending distribution which drives overspending and underestimation of expenditure. Using the data from the Financial Aggregator App we find that the main variables impacting personal finance management are the number of transactions and the skew of the payment distribution. Using an online experiment displaying numerical sequences of varying condition, set length, total, skew and standard deviation, we continue to find that set length and skew significantly impact personal finance management. This chapter raises questions regarding indirect and mediation effects of payment methods, as well as the change in the underlying spending distribution on personal finance management.

I conclude by discussing the importance of understanding the effects of newer payment methods, as well as encouraging further research to dive deeper into the underlying mechanisms driving changes in personal finance management, and understanding the additional complexity of indirect and mediated relationships between variables.

Chapter 1

Introduction

The past few decades have seen an immense growth in payment options. Options currently range from cash to PIN-verified cards and from PIN-verified cards to contactless mobile devices. Banks and other financial institutions strive to make the method of payment as easy and convenient as possible (Krol et al., 2016). Yet the ease of these payment methods might be a bigger issue than expected. Since the introduction of value-holding cards, society has moved towards being increasingly cashless, which studies find might have been to the detriment of the consumer. We will first discuss the history of payment methods, providing a context for their development, focusing on the introduction of cards, contactless cards and mobile payments. Second, we will look into the effects on behaviour associated with these newer payments. Third, we will outline how this work has contributed to the existing literature on payment methods.

1.1 Historical Overview

The UK Cards Association (2019) provides a historical overview of the development of payment methods. The first big breakthrough in the cashless society was the introduction and acceptance of metal cards in 1914. These cards gave free deferred payment privileges to customers in the US Western Union and became known as ‘metal money’. This metal card can be argued to be the first credit card known to history. From 1914 onward, multiple charge cards, like the metal card, are launched by various companies and institutions to boost sales. Examples of these are the US Diners Club, New York’s Franklin National Bank, Finders Services and American Express. It is not until 1958, however, that the term “credit card” is developed, by the Bank of America, called the Bank Americard. In 1965, the Bank of America starts licensing the use of the credit card to other banks, and the following year Barclays, a UK-based bank, launches its own credit card and in

1967 installs the first cash machine in the world, allowing credit card users to withdraw cash on their cards, solidifying the relationship between the credit card and “real” money. In the 1980s, world-wide credit cards and electronic point of sale terminals within stores were introduced. Cash and cheque were no longer the only alternatives for buying small purchases in the store. But it was in 1987 that the second breakthrough was finalised: Barclays introduced the Visa debit card. A card that directly linked to its user’s bank account and deducted the amount directly from the current balance. The next big launch for debit cards was in 1992, when MasterCard launched the Maestro as an international debit card. The debit card was a great success: in 1995, debit card ownership exceeded that of credit cards. In 1998, the debit cards accounted for more than half of all non-cash spending in supermarkets, exceeding even the popularity of the personal cheques. In 2001, card usage even exceeded cash usage in the UK, as more than half of retail spending was on payment cards. Moreover, spending had been increasingly moving online, as over 100 million card payments were made online, through the use of services such as PayPal. Three years later in 2004, it was not just in retail shopping that card usage exceeded that of cash. General UK card expenditure exceeded cash expenditure for the first time, with an average debit card user spending over £100 per week.

The cards have proven convenient and safe enough for large scale uptake. Banks saw usage and profit massively increase, even with the instatement of the Consumer Credit Act in 2005, which provides protection to consumers buying goods with their credit cards, with price limitations of £100 - £30,000. Consumers were being protected against products being sub-standard or not having been delivered. The Act also limits customer liability to no more than £50 if cards are stolen and used by someone else. However, as recent history has pointed out, the cards could be made to be even more convenient. Banks introduced the contactless card in 2007. Not using PIN-verification but a “tap&go” system, in which the card is presented to the terminal, and the terminal reads the card. To increase perceived safety, the Consumer Credit Act was extended to cover these payment methods as well, and the contactless payment was limited to £10 at the point of transaction. Contactless cards have become increasingly popular, following a development similar to that of the debit card. As its popularity grew, the limit of contactless payments has increased from its initial £10. The limit was increased to £15 in 2010, £20 in 2012 and £30 in 2015. The limit was raised to £45 in April 2020, in the early months of the coronavirus pandemic as contactless cards were perceived to be safer in terms of contamination. There have also been talks of further increasing the payment limit to £100, again to reduce chances of contamination (Financial Conduct Authority, 2021). Both the single transaction spending limit increases and the perceived reduction in health risks regarding the pandemic have spurred the popularity of contactless payments.

Statistics by UK Finance (2021) show that contactless payments accounted for half of all debit card transactions in July 2019, and that this popularity continued to grow to where contactless payments accounted for 88.6% of total card payments in 2020.

1.2 The Effect of Payment Method

1.2.1 Payment Cards

When the credit and debit cards were introduced, it was seen as progress (Rosenberg, 2005). They were argued to be progress as they had been proven to be more convenient and safer than using cheques or cash, despite possibilities of card-hacking, cloning, fishing scams, etc. (Angrisani, Foster, and Hitczenko, 2013). However, during the time of the introduction and uptake of PIN-verified cards, money was assumed to be fungible and the effect of payment method was assumed to be non-existent. It was believed that the payment mechanism had no role to play in a rational, economic evaluation of a purchase opportunity. For example, whether an item is paid for by a debit card, cash or cheque (assuming no fees involved) should not alter the perception or experience of the price or product, as they remain the same. From this reasoning stems the argument that moving towards a cashless society is a step forward (Rosenberg, 2005).

However, as the PIN-verified cards increased their market share, research started to focus on their effect on expenditure and the purchasing experience. Currently there is substantial evidence suggesting that consumers who predominantly use both debit and credit cards overspend relative to those who do not (Cole, 1998; Runnemark, Hedman, and Xiao, 2015; Soman, 2003; Tokunaga, 1993). Gross and Souleles (2002) have used the rather robust body of empirical evidence showing overspending in credit cards and have linked the cards to growing levels of debt within societies that promote their usage. This debt was argued to be driven not only by increased spending, but also a lessened awareness of spending, leading individuals to not correctly update their mental account balance and spend money “twice”. Predominant credit card usage has even been linked to impulse promotion and increased (unhealthy) impulsive behaviours (Thomas, Desai, and Seenivasan, 2011).

1.2.2 Contactless Cards

A similar lack of information about the effect of debit and credit cards is now surrounding the introduction and widespread acceptance of contactless cards, which could be seen as another step towards the cashless society envisioned by Rosenberg (2005). Figures from

the UK Cards Association (2019) indicate that the increased adoption of contactless cards and the growing popularity of mobile payment has accelerated the replacement of cash. However, this may not be progress for the financial management of the consumer, as studies indicate increased spending and reduced awareness of spending associated with this payment method.

An American study by MasterCard US (2011) showed that 70% of the contactless transactions were under \$25 and argued that most of these transactions would be a direct replacement of cash. However, the explosive growth of contactless might not be solemnly driven by cash replacement. MasterCard UK (2015) has released numbers showing that spending by British consumers using contactless cards has increased more than five-fold in one year, however the frequency of “tapping” has only doubled. This shows that consumers have become comfortable spending higher amounts with their contactless cards. At the start of 2012, when the “tap”-limit was £20, the average contactless purchase by cardholders was £4.52. Data from 2014 show that this average has increased to £7.29. These numbers drove the decision to increase the limit to £30 per transaction. The increase in spending using contactless methods of payment continued as the average spend was £9.40 in 2018 and £9.60 in 2019 (UK Cards Association, 2021). These averages have increased as the limit was raised with regards to the pandemic. The limit increase to £45 was associated with an average contactless spend of £12.38 for the whole of 2020, with individual months such as April 2020 reaching an average spend of just over £20 (Statista, 2021a). The limit increase to £100 announced in March 2021 is expected to increase the average contactless spend further, however this limit increase has not been implemented yet.

Although research indicates that people already have a strong preference for using contactless the development towards a “tap&go” or even a cashless society might not be a positive one (Rosenberg, 2005). As seen with the debit and credit card, contactless users are also prone to fall into increased spending compared to other methods of payment (James, 2017; MasterCard US, 2011; Trütsch, 2014).

1.2.3 Mobile Payments

We have seen the increased global uptake of contactless payments, with several studies associating contactless payments with increased spending and reduced spending awareness. Contactless however, is not the latest payment method to be introduced or popularised. During the writing of this thesis mobile payments have gained global popularity as well. We see the surge of payment apps such as WeChat, Alipay, ApplePay and various other e-wallets (Statista, 2020b). Although the initial mobile payment revolution came from

the East, the West is slowly catching on, predominantly relying on ApplePay, Android Pay, and traditional banks launching mobile payment platforms (Statista, 2020c). We will first look into the global uptake of mobile payment methods, followed by research studying the effects of mobile payments on personal finance management.

The introduction of mobile payments can be seen as yet another step towards the cashless society envisioned by Rosenberg (2005). Figures from the UK Cards Association (2019) indicate that the growing popularity of mobile payment has accelerated the replacement of cash as well. In 2019, the UK saw 19.1% of its transactions being made through a mobile device, at the point of sale. As a European country, it is not in the lead: the Scandinavian countries, most notably Norway (25.8%), Sweden (36.2%) and Denmark (40.9%), are the European countries in which mobile payments are most prominent. Within North America, we see that the US leads, having 29% of its transactions through mobile payments, followed by Canada with 26% of its transactions being mobile. The countries with the highest market penetration of mobile payments are in Asia, China leading with 81.1% of its transactions being through mobile payments, followed by India (37.6%) and South Korea (36.7%) (Statista, 2020d). These numbers continue to grow as the pandemic favours contactless payments, which mobile payments are a subcategory of. It remains to be seen how long it will take before payment cards will be replaced, with mobile payments becoming the dominant method of payment.

Despite mobile payment methods having been around for over a decade, little research has investigated their consequences on personal finance. Research by Garrett et al. (2014) did show that there were strong associations between mobile payment adoption and high cost debt (payday loans, auto-title loans), trouble with financial management (making ends meet), and credit card behaviour (taking cash advances and paying over the limit fees). The authors explained these results by suggesting that users of mobile payment technology were focused on convenience, and they might be prone to impulse spending. In addition, research by Meyll and Walter (2019) shows that the usage of mobile spending increases the likelihood of exhibiting costly credit card behaviours. Using a sample of over 25,000 US households from the 2015 National Financial Capability Survey (NFCS), the researchers find that mobile payment users are less financially literate and have higher levels of financial risk tolerance compared to non-users. When controlling for these two variables, the researchers find that using mobile payments is associated with a 4.9% increase in the likelihood of exhibiting costly credit card behaviour, which has been defined as only making the minimum payment, paying late fees or over the limit fees. Within the group of mobile payment users, those who use this method frequently are another 5% more likely to exhibit costly credit card behaviour compared to infrequent users. Meyll and Walter (2019) explain this increase in costly behaviour with the pain of paying

(Zellermayer, 1996).

1.3 Motivation

There is a clear lack of information and academic study exploring and explaining the impact of newer payment methods on personal finance management. In this thesis we will look at the effect of payment methods on expenditure, expenditure recall and personal financial decision-making. Work by Gross and Souleles (2002) and Raghurir and Srivastava (2008) already posed that as payment methods become more convenient, spending becomes easier and increases, the recall of expenditure becomes more difficult, and the negative consequences associated with these phenomena become more pronounced. Prior work has predominantly focused on the effect of credit cards and directed less attention towards other payment methods, such as debit cards. In this thesis we will look at two payment methods introduced recently, contactless and mobile, and study their effect on a multitude of variables associated with personal finance management, most importantly spending and spending recall.

1.4 Contributions

This thesis contributes to the literature in several ways. First, we expand the finding of different payment methods impacting personal finance in different ways to include more novel payment methods, contactless and mobile payment methods.

Second, we try to integrate our findings on the effects of contactless and mobile payments into the existing theories of payment methods, such as the pain of paying, to see if these theories can encompass all of the features associated with these newer payment methods, or whether they cannot. In Chapter 4, using an event study on transaction data, we find that the onset of contactless usage is associated with increased spending, as predicted by the pain of paying. Additionally, in Chapter 3 we find that contactless payment methods are associated with (Study 1) and cause (Study 2) reduced accuracy of expenditure recall, again in line with the pain of paying. Chapter 3, however, also tested for the mechanism driving the reduced accuracy of recall and does not find a direct or mediated role of the pain of paying. Looking at mobile payments, Chapter 5 also uses an event study of the onset of mobile payment usage, finding an increase in transactions, in line with the pain of paying, as well as significant increases in savings and cash usage, with no significant increase in spending, going against the theoretical predictions of the pain of paying. The findings of these chapters combined only partially confirm, and mainly

contradict, predictions made by theories such as the pain of paying. Our findings raise questions regarding the underlying mechanism of the changes in behaviour associated with payment methods and question the validity of the pain of paying as a theory explaining these changes.

Third, we study a complete picture of personal finance management, not looking at spending exclusively, but also explaining fee occurrence, debt accumulation, cash usage, savings and account activity. Both Chapter 4 and Chapter 5 approach contactless and mobile payments from a variety of angles. Applying an event study to the transaction data provided by a Financial Aggregator App, Chapter 4 looks at the contactless enabled and non-enabled accounts of app users who have been identified as contactless users. Looking at the contactless enabled account, we find that contactless usage is associated with a significant increase in spending (frequency and amount), cash usage and savings, but has no significant on overdraft, unsecured loans and credit use. These effects persist on the user level. The majority of the significant increase in spending and savings can be explained by additional money being transferred into the contactless enabled account. Again applying an event study, Chapter 5 looks at the mobile enabled and non-enabled accounts of app users who have been identified as mobile payment users. Looking at the mobile enabled account, we find that mobile payments are associated with a significant increase in spending (both frequency and amount), cash usage and savings. The increase of total monetary means used on the mobile enabled account is partially explained by changes on the non-mobile enabled account, which shows decreases in all the variables showing increases on the mobile-enabled account. Due to this compensatory mechanism, the increase in spending associated with mobile payments loses significance on the user level. Overall, we do find that newer payment methods increase spending frequency, and to some extent spending value and lead to increased usage of the enabled account, but that they do not seem to be associated with changes in overdraft, debt, or credit card use, painting a full picture of their possible effects.

Fourth, we find a shift in account usage not indicated by any prior literature. In Chapter 4 we find the increase of total monetary means (spending and saving) used on the contactless enabled account to exceed £100. This increase cannot be explained by changes on the non-contactless enabled account. Further analysis reveals that contactless enabled accounts receive significantly more money transferred into the account from other accounts of the user not registered on the Financial Aggregator App, explaining approximately 70% of the increases in spending and saving associated with contactless usage. Our results also show a shift in account activity, with the contactless account becoming more active, at the expense of other accounts. Despite this compensatory mechanism, approximately 30% in increased spending remains unexplained and can be attributed to the onset of contactless

usage. In Chapter 5 we find a similar compensation mechanism for mobile payments, but see that it is the visible and registered non-mobile account compensating for the increased activity of the mobile account. We do continue to find a significant increase in the number of transactions and savings, showing that this compensation mechanism cannot explain the increase in usage fully. Our contribution in this shift in account activity is unique, as no prior research has indicated such a shift in account usage to occur, to our knowledge.

Fifth, we go beyond the study of direct effects of payment methods on personal finance and also assume the possibility of indirect effects, where different payment methods change the shape of the spending distribution, impacting personal finance management through a shift in perception of the spending distribution. In Chapter 6 we use the Financial Aggregator App data and find that the main variables associated with personal finance management are the number of transactions and the skew of the distribution. To establish a causal relationship we conduct an online experiment displaying 20 numerical sequences varying condition, set length, total, skew and standard deviation. We continue to find that set length and skew are the main factors impacting personal finance management. Most payment methods increase the number of transactions often favouring smaller expenses, skewing the spending distribution more positively. The effect of payment methods may be more indirect than expected. Our research establishes this indirect relationship and raises questions regarding indirect and mediation effects of payment methods, as well as the effect the shift in the underlying spending distribution may have on personal finance management.

Sixth, we contribute to the literature using a multi-method design, having conducted observational studies, experiments and data analysis on data from a Financial Aggregator App. This multi-method design continues the trend of using multiple methods within a single paper to be able to establish both proof of concept as well as a causal relationship, increasing the external validity of the results. We have done exactly that.

Seventh, we work with exclusively British data, as compared to most research having been done in the US. This is an advantage as both contactless and mobile payment methods have been popularised within the UK, but remain to find solid footing within the US.

Chapter 2

Literature Review

The aim of this dissertation is to establish whether contactless and mobile payments impact personal finance management. Prior work on earlier payment methods, such as credit cards and debit cards, has shown there to be an effect of payment method. We will first discuss this work to contextualize our hypotheses with regards to contactless and mobile payments, followed by a discussion of the research already conducted on contactless and mobile payments. Second, we will discuss the theories explaining the behaviours associated with different payment methods. The theories of interest are those of the pain of paying, transparency, decoupling and multi-functionality. Third, we will dedicate an entire section to the study of expenditure recall. Fourth, we will discuss the research done on distributions, spending distributions specifically, proposing that payment methods do not directly, but indirectly impact personal finance management through changes in the spending distribution. Last, we will summarise the literature to provide a concrete overview of the work done. We will first focus on the empirical work on a variety of payment methods.

2.1 Payment Methods

The effect of payment method has long been established. Various studies have shown there to be an effect of payment method, when comparing credit cards to cash. Credit cards were found to have a higher expenditure at the point of sale (Hirschman, 1979; Feinberg, 1986; Prelec and Simester, 2001; Raghubir and Srivastava, 2008; Soman, 2003; Tokunaga, 1993; See-To and Ngai, 2019), worsened expenditure recall (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; See-To and Ngai, 2019), lower product connectivity (Shah et al., 2016), increased benefit focus (Chatterjee and Rose, 2012), reduced impulse control (Thomas, Desai, and Seenivasan, 2011), and increased debt accumulation (Gross

and Souleles, 2002). Looking at debit cards, a study by Runnemark, Hedman, and Xiao (2015) finds an increased willingness to pay, when compared to cash. Research by Lee, Abdul-Rahman, and Kim (2007) shows that households with revolving debt are more likely to use debit cards. And research by Shah et al. (2016) also shows lower product connectivity comparing debit cards to cash. These are the only three studies known to the authors to focus on debit card usage, rather than credit card usage. In this thesis we will make continuous reference to this evidence base, however, this evidence base does warrant further explaining to contextualise its findings. We will discuss the effects in turn, starting with credit cards, and their effects on spending, followed by expenditure recall, and other more miscellaneous findings. Following from credit cards, we move onto debit cards, finishing with a discussion of the limitations of this evidence base, before we move onto contactless and mobile payments.

2.1.1 Credit Cards

The main finding established with credit cards is that they are associated with an increase in spending or increased willingness-to-pay, as compared to cash. We will discuss the seminal work by first looking at observational studies, before moving onto experiments.

Hirschman (1979) was one of the first to establish increased spending by showing that customers of a U.S. department store who paid with either their bank card (credit) or the store-issued credit card paid for larger total dollar purchases in the department store, as compared to customers who used cash. Soman (2003) used real transaction data from a U.S. supermarket, by collecting 275 grocery store receipts from shoppers that volunteered them. He finds that shoppers who use credit cards spend more compared to those who use cash. Other studies have also found increased grocery store spending when looking at the difference between credit card and cash users (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011). Feinberg (1986) observed tips left by cash and credit card customers in a restaurant. Those who tipped by credit card tipped significantly more than those who tipped by cash or cheque. Tokunaga (1993) aimed to develop an integrative profile of people with credit-related problems. Through the use of self-report questionnaires Tokunaga found that unsuccessful credit users displayed greater external locus of control, lower self-efficacy, viewed money as a source of power and prestige, took fewer steps to retain their money, displayed lower risk-taking and sensation-seeking tendencies, and expressed greater anxiety about financial matters than successful users. All of these studies are observational in nature and show there to be increased spending for those who use credit cards as compared to those who use cash.

Looking at experimental work we find that participants were often put in either a credit card or cash condition, by having them pay with said method, or by having credit card paraphernalia present such as an insignia or logo. Feinberg (1986) conducted four experiments to show the effect of credit cards. He showed that estimations of the willingness to pay (Experiment 1 and 2) or the willingness to donate (Experiment 3) were significantly higher for participants who had a credit card insignia (MasterCard) present when doing these estimations, compared to the other group who did not have the insignia present. Experiment 4 complements Experiment 3 by having the participants actually make the donation, and continues to find that those who had credit card stimuli present donate significantly more to charity than those who did not. Research by Raghubir and Srivastava (2008) also selected participants into groups with, or without, the presence of a credit card logo. Participants with the credit card logo present estimated a significantly higher willingness to pay for a set of nine menu items for a new restaurant in town (Study 1), and estimated a significantly higher budget for preparations for a Thanksgiving party (Study 2). Studies 3 and 4 focus on the difference between cash and “scrip” (stored value certificate), showing that consumers also spend more when they are spending scrip versus cash of the same value. Research by Prelec and Simester (2001) showed that the willingness-to-pay for items was higher with credit cards than with cash, when auctioning off tickets to a sold out sporting event (Study 1) or a \$175 dinner certificate (Study 2). Work by Soman (2003) showed that participants paid more for photocopying when using a pre-paid card compared to cash (Study 1). He also observed people in a “natural experiment” (p. 177), studying two laundry rooms of two major apartment complexes, in which one laundry room changed its payment mechanism. Both rooms initially accepted coins, but one of the complexes upgraded to accepting prepaid laundry cards. Despite there being no price change, consumers using the prepaid card system spend significantly more on laundry than those who used cash. The experimental evidence is in line with the observational studies: credit cards increase spending and willingness to pay as compared to cash.

In addition to increasing spending and willingness to spend, credit cards have also been associated with reduced accuracy of expenditure recall. Srivastava and Raghubir (2002) showed, through the use of a survey, that total expenditure recall was significantly worse in participants who used credit cards as compared to cash, but that the gap in recall accuracy could be reduced by having participants not recall the total as a whole, but in different spending categories. Work by Gross and Souleles (2002) made use of a data set on credit card accounts to establish that a lot of credit card users go over their limit, as they forget smaller prior expenditures and end up spending money “twice”. See-To and Ngai (2019) approached shoppers at six different supermarkets from different regions

in Hong Kong. Shoppers were approached after they had done their grocery shopping and asked to fill in a survey regarding their shop as well as give up their receipt. This research revealed that shoppers who paid by credit card had spent significantly more than those who used cash, and that those who had spent more had significantly worse recall of their expenditure. Additionally, the reduced accuracy of recall was also found to be positively correlated to an increased willingness-to-pay for further shopping. This study confirms both reduced recall accuracy on credit cards, as compared to cash, as well as finding higher spending credit cards, as compared to cash.

Credit cards have also been associated with reduced product attachment, increased focus on product benefit and increased impulsiveness. Shah et al. (2016) showed that participants who paid by credit card attributed significantly lower value to a mug they just purchased and rated their emotional connection to the mug as significantly lower. This result also replicated for donating \$5 to charity, by using either cash or a voucher. Those who donated using the voucher rated their psychological connection to the charity as significantly lower. Moving from product connection to focusing on product benefits, Chatterjee and Rose (2012) showed that consumers who use credit cards focus more on product benefits as compared to those who use cash. After having gone through a sentence scrambling task with words related to either cash or credit card, participants were shown three benefits and three cost features (costs = financial, benefits = product attribute related) of a camera, as well as the camera itself and then asked to indicate their reservation prices. Participants primed with credit cards had a significantly higher reservation price for the camera (Study 1), could identify more benefits related to a product rather than costs (Study 2), and responded to benefits significantly quicker when evaluating an iPhone as well as having a significantly higher reservation price for the iPhone (Study 3). Work by Thomas, Desai, and Seenivasan (2011) shows that consumers who use payment cards for their grocery shopping, as compared to cash, buy significantly more unhealthy food products. This finding was established by analysing the actual shopping behaviour of 1,000 households over a period of 6 months, revealing that shopping baskets have a larger proportion of food items rated as impulsive and unhealthy when shoppers use credit or debit cards to pay for the purchases. Additionally, they conducted three experiments to establish the effect of credit cards on spending and impulsivity, finding that participants who have credit card logos present in an online food shopping study spent significantly more on groceries, spent significantly more on vice products, and had reduced accuracy of expenditure recall, compared to those who did not have the credit card logos present (Experiment 1). Experiments 2 and 3 also make use of the online shop, showing that participants spend more in general, more on vice products, and reported significantly lower levels of the pain of paying in the credit card condition. However, the

accuracy of recall did not vary across payment methods, contrary to evidence by Gross and Souleles (2002), See-To and Ngai (2019), and Srivastava and Raghurir (2002). In Experiment 3 participants were also asked to complete the Spendthrift-Tightwad (ST-TW) scale developed by Rick, Cryder, and Loewenstein (2008) showing that payment method had a significant effect on Tightwads' (low ST-TW score) purchase decisions: they were more likely to buy impulsive products when paying by credit card. This effect did not exist for Spendthrifts (high ST-TW score). Last, looking into debt accumulation we have already discussed the research by Gross and Souleles (2002) who employ a credit card account data set to establish that those who use credit cards have higher forms of debt.

2.1.2 Debit Cards

Although most research has focused on credit cards, a small amount of work has focused on debit cards, comparing their effects to those of cash. Runnemark, Hedman, and Xiao (2015) show that willingness to pay is higher when participants pay with debit cards when bidding for three products (regular coffee, expensive coffee and beer), as compared to cash. This effect persists even when controlling for cash-on-hand constraints, spending type, price familiarity and consumption habits of the products. Shah et al. (2016) show that participants who paid by debit card reported significantly lower connection to the headphones they had been asked to purchase, as compared to those who paid by cash. Additionally, participants had also been asked to rate their pain of paying. Participants who had used debit cards for their purchase reported significantly lower levels of the pain of paying. Lee, Abdul-Rahman, and Kim (2007) focus on analysing debt accumulation with debit card usage. Conducting simultaneous equation modeling on the 2004 Survey of Consumer Finances, they examine how debit card users are different from non-users, and whether debit card usage influences household debt. They find two key results. First, that the use of debit cards is negatively associated with household debt, after controlling for selection bias. Second, that those with revolving debt tendencies (i.e., carrying outstanding balances on credit cards) are more likely to use debit cards than those without a revolving debt tendency. They argue that debit card usage discourages the accumulation of household debt rather than that debit card users tend to be financially conscientious. The finding that the use of a card payment method reduces household debt accumulation goes against findings by Gross and Souleles (2002), although these findings are related to the credit card. The little work that has been done on debit cards does seem to indicate that similar effects, increased willingness to pay, reduced product connection,

reduced pain of paying, exist within both methods. Fortifying the idea that there is a difference between payment cards and cash, regardless of the concurrency of payment.

Limitations

There are several limitations within this existing evidence base. Due to the majority of these studies having been conducted comparing credit card usage to cash, the results cannot be seamlessly extrapolated to fit other payment methods, due to a differentiation in characteristics (e.g. concurrency, shape, speed). This becomes exceptionally clear when contrasting results from Gross and Souleles (2002) to those of Lee, Abdul-Rahman, and Kim (2007). Additionally, several of these studies are based on surveys or observed data, and as such correlational in nature. This means they cannot be extended to explain causal effects or relationships. Lastly, the studies that were causal in nature, i.e. lab experiments, were often conducted on student samples, a subset of the population which cannot be argued to be representative. Additionally, there is literature indicating issues with the external validity of results found exclusively in lab settings (Galizzi and Navarro-Martinez, 2019). In this thesis we aim to expand on this evidence base by incorporating newer payment methods, a mixed methodology allowing us to make causal inferences whilst perserving high external validity, and make use of representative samples.

2.1.3 Contactless Cards

While contactless payments were already in use at the end of the last century, they have now become a global phenomenon, accounting for a large share of transactions. However, the development, integration and uptake of contactless has not been equally spread globally. Its main areas of prevalence are Australia, the United Kingdom, Canada, Western Europe and to a lesser degree the U.S. We will discuss the prevalence of contactless, its relation to cash and its effects on personal finance management. Studies find an increase in spending as well as a reduction in spending awareness, when looking at contactless usage.

In Australia, this process of moving towards a cashless society has been well documented due to the triennial Consumer Payments Survey (CPS) by the Reserve Bank of Australia. Having been conducted initially in 2007 and followed by those in 2010, 2013 and 2016, the CPS shows the uptake of contactless. The surveys of 2007 and 2010 already showed a decline in cash usage, falling from 70% to 64% and a decline in cash withdrawals, falling by 6% (Bagnall and Flood, 2011). A link was made to contactless usage, but due to its novelty and the initially slow uptake, the report does not elaborate on the

effects of contactless. The 2013 and 2016 survey corroborate this link better, and have entire sections devoted to contactless card payments (2013, 2016) and mobile payments (2016). The 2013 CPS shows a continued decrease in cash usage (from 64% to 47%), and a rise in card usage (Ossolinski, Lam, Emery, et al., 2014). This trend has persisted for all types of purchases, products and purchase values. Part of this is explained by the increase in card terminals at the point of sale. This increase was 35% over the 2007-2013 period. Contactless as a payment method has been widely adopted in Australia since 2010, with two-thirds of respondents indicating they had a contactless card (Bagnall and Flood, 2011). This has contributed to cards being used at the point of sale, with 22% of card payments at the point of sale being made by contactless cards, compared to 26% signature-based credit card payments and 20% PIN-verified debit card payments. The share of contactless card payments was highest under \$10 (AUD), making up for 34% of the payments. Contactless was used for 20% of the payments between \$50 and \$100. The median value of a contactless payment was \$26, compared to “contact” payments having a median of \$37 (Ossolinski, Lam, Emery, et al., 2014). The 2016 CPS indicates continued contactless payment method uptake, having collected 17,000 payments by 1,510 respondents over a week (Doyle et al., 2017). Card usage has overtaken cash as the dominant method of payment across all groups for the first time. Contactless usage also continues to increase, displacing cash for many lower value transactions. Close to 60% of respondents made at least one contactless payment per week. Contactless usage, however, declines with age, as participants over 65 years of age continue to prefer cash. The survey showed that the preference for cash was motivated by it being used as a budgeting tool. Despite this, the majority of respondents (55%) did not top up on cash during this week. Overall, contactless as a method of payment has seen an increased popularity in Australia over the 2007-2016 period, displacing cash mainly in the lower value transactions.

Research in Canada shows similar trends. Fung, Huynh, and Sabetti (2012) show that contactless credit cards have led to a reduction of 14% in the cash ratio in terms of value, and 13% in terms of volume. Stored-value cards, such as debit cards, have led to a decrease of 12% in the cash ratio in terms of value, and 15% in terms of volume. So contactless is in fact displacing cash, especially in grocery stores, where contactless cards are used for 56% of transactions and at gasoline stations (24%). The researchers do argue that as their numbers are based on data collected mainly in 2009, when the contactless cards were still in nascent stages of deployment, they might underestimate the current impact of contactless cards on cash usage.

In the US a similar trend can be spotted. However, work in the US links the contactless payments to increases in expenditure. A 2011 study by MasterCard produced results showing an increased usage of Mastercard’s PayPass (classed as contactless) both in terms

of value spending and transaction frequency. The overall results were a 30% increase in expenditure and an almost 50% increase in transaction frequency using cards (MasterCard US, 2011). Looking deeper into this claim we find that these increases are mainly due to cash replacement. More than 70% of the transactions were under \$25, a fact that MasterCard acknowledges later in their report. Moreover, the study was conducted measuring the year-over-year growth for accounts that conducted “tap” transactions within the same 3-month time frame, but only sampled from three issuers. Lastly, the conducting of this research could suffer a strong bias as it also serves as a sales argument for merchants and the data is restricted to MasterCard customers only. Research by Bradford (2005) for the Federal Reserve Bank of Kansas also finds an increase in expenditure per transaction, when using contactless. Here, the value difference is 20%, when comparing cash to contactless card usage for the retailer CVS. Most studies do not replicate differences this high. This could potentially be due to the specific retailer, or the fact that contactless as a method was still new to the States. Trying to replicate findings showing an increase in spending for contactless, Trütsch (2014) uses the 2010 Survey of Consumer Payment Choice to estimate the impact of using contactless cards on the spending ratio at the individual level. Using propensity score matching to control for selection, the estimation shows that using contactless has a significant effect for both credit and debit cards. In agreement with MasterCard US (2011), the analysis found an increase in expenditures, however the increase was much smaller. For credit cards, the usage of contactless led to an increase in the spending ratio of 8.3% at the point of sale, while the effect for retail and services purchases was 4.8% and 3.5%, respectively. For debit cards, the usage of contactless led to an increase in the spending ratio of 10% at the point of sale. The effect on retail and services payments resulted in a 4.5% increase. Seemingly, the effect of contactless holds stronger for debit cards than it does for credit cards. Trütsch (2014) did not elaborate on whether these increases were due to the replacement of cash, or whether individuals are distinctly spending more, without replacement occurring.

In the UK, it was estimated that cash would be quickly replaced by contactless cards (Lacmanović, Radulović, and Lacmanović, 2010). Consumers predominantly used cash for all their lower value transactions, as 80% of cash usage was for purchases of less than £10.00. The researchers argued that due to its increased speed, convenience, security and privacy, compared to cash, contactless would swiftly replace it. Due to the same characteristics, however, they warn that contactless makes it easier to spend than cash does. They do not elaborate on this point. Data seems to support the first point made by Lacmanović, Radulović, and Lacmanović (2010). Contactless cards were used for 52% of in-store payments and other contactless devices were used for 11% of in-store payments in 2018 (Campbell, 2015). Average spending with contactless methods has also crept

up, being £4.52 at the start of 2012, £7.29 in 2014, £8.40 in 2016, £9.40 in 2018, £9.60 in 2019 to £12.38 in 2020 (UK Cards Association, 2019). Research by James (2017) supports the second point made by Lacmanović, Radulović, and Lacmanović (2010) as well, showing that contactless usage does provide consumers with the feeling of easier spending. Making use of semi-structured interviews and thematic content analysis, James found a significant effect on spending habits, with the common theme being the lack of association between tapping a card and handing over cash. Most participants argued that contactless transactions did not feel like “real” money, in the way that a cash payment did. These findings are in line with the Monopoly Money Effect as proposed by (Raghubir and Srivastava, 2008). Moreover, using contactless also gave participants a reduced sense of guilt, as they did not perceive the use of contactless as an actual payment. Lastly, participants also experienced a sub-conscious accumulation of small, impulsive purchases when using contactless payment. This evidence is in line with research Gross and Souleles (2002) who found a similar effect for credit card debt accumulation through the mis-remembering of multiple small expenditures.

Overall, we can see that there is a strong preference for using contactless cards in the global areas that they have been introduced in, due to their speed, convenience and safety, especially when compared to cash. Contactless seems to be most popular as a cash replacement, due to being used mostly for low value transaction that are normally paid for in cash. This would be a direct explanation for the decrease in cash usage that has been described above. This preference is strongest amongst the younger generations, whereas those over 65 years of age might still prefer using cash. It has been argued that a preference for cash might present itself as an opportunity for improved budgeting. Research has also indicated an increase in spending when paying using contactless cards as well as tendency to feel as if one is not spending “real” money.

2.1.4 Mobile Payments

We have shown in the previous sections that there is an effect of payment method on personal finance management, especially in terms of spending and expenditure recall. The few studies looking at contactless payments find similar effects to those associated with debit and credit cards. However, there is more to contactless than contactless cards. Mobile phones also have the option of being used as a contactless payment device and have enjoyed widespread global uptake due to their ease of usage, especially as most people do not leave the house without their mobile devices, increasing the availability of money through constant access.

We have seen a surge of payment apps such as WeChat, Alipay, ApplePay and various other e-wallets (Statista, 2020b). Although the initial mobile payment revolution came from the East, the West is slowly catching on, predominantly relying on ApplePay, Google Pay, and traditional banks launching mobile payment platforms (Statista, 2020c). It remains to be seen how long it will take for payment card usage to decline and mobile payments becoming the new normal. Figures from the UK Cards Association (2019) indicate that the growing popularity of mobile payment has accelerated the replacement of cash. In 2019, the UK saw 19.1% of its transactions being made through a mobile device, at the point of sale. As a European country, it is not in the lead: the Scandinavian countries, most notably Norway (25.8%), Sweden (36.2%) and Denmark (40.9%), are the European countries in which mobile payments are most prominent. In North America, we see that the US leads, having 29% of its transactions through mobile payments, followed by Canada with 26% of its transactions being mobile. The countries with the highest market penetration of mobile payments are in Asia: China leads with 81.1% of its transactions being through mobile payments, followed by India (37.6%) and South Korea (36.7%) (Statista, 2020d).

Due to their increased global uptake, mobile payments have received increased attention in research. Meyll and Walter (2019) show that the usage of contactless mobile spending increases the likelihood of exhibiting costly credit card behaviours. Using a sample of over 25,000 US households from the 2015 National Financial Capability Survey (NFCS), the researchers find that contactless mobile users are less financially literate and have higher levels of financial risk tolerance compared to non-users. When controlling for these two variables, the researchers find that using contactless mobile payments is associated with a 4.9% increase in the likelihood of exhibit costly credit card behaviour, which has been defined as only making the minimum payment, paying late fees or over the limit fees. Within the group of contactless mobile payment users, those who use this method frequently are another 5% more likely to exhibit costly credit card behaviour compared to infrequent users. Meyll and Walter (2019) explain this increase in costly behaviour with the transparency framework (Soman, 2003) and the pain of paying (Zellermayer, 1996), theories which will be explained later.

Research by Garrett et al. (2014) also showed strong associations between mobile payment adoption and high cost debt (payday loans, auto-title loans, etc.), trouble with financial management (making ends meet), and credit card behaviour (taking cash advances and paying over the limit fees). The authors explained these results by suggesting that users of mobile payment technology were focused on convenience, and they might be prone to impulse spending.

Research by Falk et al. (2016) focused on the link between the overall price image in

retail stores and the method of payment. They conducted three empirical studies to find if the method of payment impacted overall price image and whether the method of payment impacted the willingness to pay. First, they found that higher transparency, as defined by Soman (2003) led to a higher overall price image. This means that the store is perceived as being expensive. A low price image tends to indicate value for money and has been linked to high levels of store loyalty. Cash led to a high and therefore unfavourable price image, whereas card and mobile payments did not. Second, they found that willingness to pay was higher when using contactless mobile, compared to both card and cash. The effect was strongest when compared to cash.

Overall, we do see that there is a growing preference for using mobile payments, due to their speed, and availability, especially when compared to cash. We also see a link between mobile payments and debt accumulation, which warrants further exploration.

Continuing from the evidence outlined above, the next section will look at frameworks that can explain the effect(s) different methods of payment can have and how this can be applied to the results seen so far in contactless and mobile methods of payment.

2.2 Frameworks Explaining the Effects of Payment Methods

The effect of payment methods on various aspects of personal finance management has been long standing. Within this section we will look into several frameworks explaining why different payment methods have the effects that they do, and how, if at all, they apply to contactless and mobile methods of payment. We will start of with the pain of paying, followed by transparency, decoupling and multi-functionality.

2.2.1 Pain of Paying

The dominant theory in explaining the difference between payment methods is that of the “pain of paying”, in which different methods of payment influence the way consumers feel about the payment (Zellermayer, 1996). When using cash, consumers experience a robust amount of negative feelings during the transactions. These negative feelings are invoked by the physical handing over of the cash, the representation of value that cash signals and the concurrency of payment with the receiving of the good or service paid for. The reason these three aspects matter to the pain of paying is due to their influence on the ease and friction of the payment. Paying with cash is a long process, with the frictions of having

enough cash, counting cash, handing it over, receiving some back etc., whereas paying by card has much less friction; there is no need for counting, nor exchanging hands. The card just gets swiped or tapped (in case of contactless), maybe a PIN needs to be entered. It is easier and faster. As a result, card payments are less painful.

So what is needed for a “painful” payment is physicality, value representation (transparency) and concurrency (coupling) (Zellermayer, 1996). Different payment methods score differently on these criteria and the observed increase in spending when using credit card compared to cash is then simply explained by different levels of pain. The more pain experienced, the less is spent. This simple statement seems to be supported by many studies, as they have found that spending and willingness to pay is much higher using any other payment method than cash (Feinberg, 1986; Gross and Souleles, 2002; Hirschman, 1979; MasterCard US, 2011; Prelec and Simester, 2001; Raghurir and Srivastava, 2008; Runnemmark, Hedman, and Xiao, 2015; See-To and Ngai, 2019; Soman, 2003; Tokunaga, 1993; Trütsch, 2014; See-To and Ngai, 2019). Zellermayer (1996) ran five studies in his dissertation corroborating the pain of paying. We will focus on two of these which are most relevant to our topic of study: when would consumers like to pay for their purchases, before or after the consumption? And what kind of payment method do consumers prefer for making payments?

With regards to the timing of the payment in relation to purchase, Zellermayer found a strong preference for paying before consumption rather than after consumption. According to the results from his survey, paying for an already consumed good is much more painful than paying for a good that has yet to be consumed. Following similar reasoning, making continuous payments, e.g. monthly rent, is more painful than paying under the expectation of a single payment, regardless of the increased size of paying the whole sum at once. Zellermayer argues that the least painful should be a payment that will generate or is expected to generate additional utility. An example for this is reducing current expenditure by saving a set amount of money per month, which is often seen with people trying to save for their Christmas shopping. Given that this is done with anticipated utility, this form of current expenditure reduction is not very painful, especially when compared to having to pay-off an already enjoyed vacation, when there is no longer the consumption to look forward to. The timing of the payment is especially relevant for credit card payments, where the actual “loss” of money occurs after the good or service has typically already been consumed.

With regards to preference for payment methods, Zellermayer’s survey (1996) showed that a clear majority of the participants preferred paying by cheque. However, this was over 2 decades ago, and in 2021 barely anyone uses cheques as a method of payment. Discarding this result, the second preferred method of payment was the credit card, followed

by cash as a third preference. Preferring paying with credit cards over paying with cash does seem to indicate that paying with cash is more painful, and that participants would like to avoid this pain, explaining the popularity of newer payment methods that were found to be less painful such as the credit and debit card.

The pain of paying, as proposed by Zellermyer, focuses almost exclusively on spending, but has been used to explain effects of reduced spending awareness as well (Srivastava and Raghubir, 2002). It is reduced spending awareness in which we are increasingly interested, as it is reduced awareness that has been linked to increased debt accumulation (Gross and Souleles, 2002). Gross and Souleles (2002) propose that if people cannot recall their spending accurately, they will not be able to update their mental account balance. As such, there will be a change in the actual account balance, but not in the mental account with which the consumer keeps track of their spending on that specific account. This makes it possible for consumers to spend their money “twice”. The consumer did not remember having spent money already and as such spends it again. This leads to people hitting their overdrafts and getting into debt on their real accounts, before they thought they would according to their mental accounts. As such, when mental accounting of this type is made more difficult through reducing a payment’s memorability or salience, for example by reducing the pain of paying, the likelihood of hitting overdraft increases.

The pain of paying is the dominant theory in explaining the different behavioural outcomes associated with different payment methods. A prominent number of studies mentioned before point to the pain of paying as the driving mechanism behind their findings (Chatterjee and Rose, 2012; Prelec and Simester, 2001; Prelec and Loewenstein, 1998; Raghubir and Srivastava, 2008; Runnemark, Hedman, and Xiao, 2015; See-To and Ngai, 2019; Shah et al., 2016; Thomas, Desai, and Seenivasan, 2011). Several neuroscientific studies also support the pain of paying, showing that the levels of pain experienced can greatly predict whether a consumer is willing to buy a product (Knutson et al., 2007; Mazar et al., 2016). Knutson et al. (2007) showed that if the increase in activity in the insular cortex - associated with the experience of physical pain - was higher than the increase in activity in the striatum - associated with (anticipated) reward - that the purchase would not occur: the pain of paying was too high. Research by Rick, Cryder, and Loewenstein (2008) showed that there were individual differences between people who experienced high levels of pain of paying (tightwads) and low levels of pain of paying (spendthrifts) regardless of payment method used. The pain of paying has a neural basis in the brain.

The evidence supporting the pain of paying is predominantly driven by studying the different neural patterns when deciding to purchase. However, more recent neuroscientific

evidence questions the role of the pain of paying. Plassmann, Mazar, and Rangel (2011) found increased insular activity when participants were exposed to electric shocks, but not when they had to pay for an item they just won at an auction. In addition, Banker et al. (2017) rejects the longstanding idea of credit cards reducing the pain of paying, by explicitly studying purchasing decisions when paying by credit card or cash. They found that shopping with credit cards did not lower pain of paying (exaggerated deactivation in the right Anterior Insular Cortex) during a transaction, but found that credit cards appeared to generally facilitate greater reward sensitivity, rendering consumers less sensitive to price information.

This evidence raises questions as to the validity of the pain of paying in explaining the different behavioural outcomes with regards to using different payment methods. The reduced price sensitivity found may work for all payment methods that increase convenience. Contactless cards have been introduced to be quicker and more convenient (Trütsch, 2014), as have mobile payments. The pain of paying may not be the mechanism explaining the different behavioural outcomes. As such, we turn our eyes to other theories.

2.2.2 Transparency

Soman (2003) attributed the effects of different payment methods to their different levels of “transparency”. A method is more transparent the more it allows the user to keep track of how much is spent and how much is left to spend. Soman has ranked the different methods of paying in terms of transparency. He argued cash to be the most transparent form of money, for both its status as legal tender and its salience in both physical form and amount. Cash in its physical form can only be handed over once, and once it is handed over the consumer is no longer able to hold it in their hand. Moreover, cash is (most frequently) handed over concurrent with the purchase made. There is therefore a direct exchange between physical money and the item/service purchased. The fact that cash also directly shows its value as a legal tender and comes in different shapes, materials and colours representing different amounts of value, makes it even more salient. Research has shown that “breaking” a 50-pound note into smaller denominations due to a purchase invokes negative feelings within the person having to do so, and might actively discourage spending because of the negative feelings associated with this (Raghubir and Srivastava, 2009).

In contrast to the salience of cash, different payment forms such as the credit and debit card have been ranked much lower in terms of transparency. Cards do not share the meaning and feelings invoked by its physical form as compared to cash. A debit or credit card is, after all, only a plastic card. Although linked to money, its physical

form fails to represent this. Whether it is tapped against the machine or inserted with PIN-verification, it does not have the same physical exchange of cash for goods/services. According to Soman, the credit and debit card are equally low in transparency, and are the payment methods that are ranked lowest in terms of transparency. In conclusion, cash is more transparent than credit cards, hence resulting in lower spending, more accurate recall and more effective budgeting.

It is important to understand what it means to be ranked the lowest in terms of transparency. Soman used this as a measure for indicating to what extent the consumer thinks of spending “real” money. The less transparent a payment method is, the less it feels like “real” money. He used his framework to explain why people spent more using pre-paid cards and credit cards as compared to cash (Soman, 2003). James (2017) showed that when people feel like they are not spending “real” money, the more money gets spent, and the less salient those expenditures are. Participants actively stated that they felt “less in control of their finances”. Less transparent payment methods are linked to worse personal finance outcomes such as increased spending, reduced accuracy of expenditure recall and reduced control over one’s finances.

2.2.3 Decoupling

Whereas transparency focuses predominantly on form, the theory of decoupling focuses on payment concurrency (Srivastava and Raghubir, 2002). Decoupling is the (temporal) distance between a transaction and the resulting money outlay. The emphasis is on the salience of the resulting benefits and costs. For someone who pays by cash, the payment is more easily juxtaposed to the benefits of consumption, whereas someone who pays by credit card will enjoy the benefits of consumption whilst the cost of post-payment will be distant in the future. By reducing the salience of the money outlay, post-payment may make people less likely to pay attention to how much they are paying, hence less likely to recall the expenditure and more willing to spend.

In terms of decoupling, credit card payments are ranked lowest in terms of salience, as transaction and payment are decoupled. Other concurrent forms of payment, such as cash and debit card, are ranked higher in terms of salience, as the payment immediately follows the transaction.

However, in later work Raghubir and Srivastava (2008) do distinguish spending with cash from spending on cards. They argue that spending when using debit and credit cards may seem like “play” money or “Monopoly Money” (e.g. not “real” money. This is their reasoning for why using the cards makes it easier to spend. It does not feel or

appear as real as the legal tender (cash), therefore reducing the salience that is seen with the parting of “real” money. This is in line with work by James (2017)

2.2.4 Multi-functionality

All the aforementioned theories were proposed when payment methods had one functionality, they could only be used as payment methods, they had no other function. However, the introduction of mobile payments changed this: mobile devices have multiple functions, of which one is being a payment method, making them multi-functional. This shift toward multi-functionality in payment modes is assumed to reduce payment salience and consequently decrease consumers’ recall accuracy of past expenditures. This would relate to the salience of payments discussed in the previous sections. A mobile device is a hyper-multi-functional device, its payment function not being heralded as its main function. It is possible that this hyper-multi-functionality reduces the salience of the device as a payment method, and the individual transactions associated with it.

Research by Gafeeva, Hoelzl, and Roschk (2018) finds that recall accuracy is lower when using a single- or a multi-functional card than cash, a multi-functional card being a card which bundles payment with non-payment functions (e.g., loyalty programs, identification, and other information functions). However, they also find that it is not the multi-functionality of the card that results in a higher recall error but the individual usage patterns: a higher usage frequency of the non-payment functions results in a higher recall error. Carrying this finding over to mobile spending, the main function of a mobile device not being payment, we expect there to be an effect of reduced salience compared to any other payment method, predominantly cash.

2.2.5 Theoretical Overlap

There is clear overlap between the theories. And as time progressed, most researchers studying different payment methods and their respective effects have integrated these theories together to explain those effects. This includes the aforementioned researchers who proposed the theories.

Raghubir and Srivastava’s (2008) decoupling links to the pain of paying, where the levels of payment coupling are used to determine the amount of pain caused by the different methods of payment. In the case of purchases paid by cash, there is a tight coupling of purchase and payment, as the purchase is immediately followed by the payment. This accentuates the pain of paying. With credit card purchases, although the payment also immediately follows after the purchase, the actual parting of the money occurs much

later than the purchase, thereby decreasing the pain of paying. The observed increase in spending when using credit card compared to cash, is then simply explained by different levels of pain. The more pain experienced, the less is spent. This simple statement seems to be supported by many studies, as they have found that spending and willingness to spend is much higher using credit cards than cash (Cole, 1998; Prelec and Simester, 2001; Raghubir and Srivastava, 2008; See-To and Ngai, 2019; Soman, 2003; Thomas, Desai, and Seenivasan, 2011; Tokunaga, 1993).

Another interesting point made by Raghubir and Srivastava (2008) is how well people can estimate their future pain of paying. They argue that the increased spending that is seen within credit card usage might also be a result of the underestimation of the future pain of paying. This underestimation is a result of the estimation of pain being mitigated by the immediate gratification of the purchase. This reasoning provides another argument for why credit cards are experienced as less painful and seem to lead to higher expenses.

Gross and Souleles (2002) have also argued that there is a mitigating factor when the future pain of paying is estimated in credit card usage. Instead of immediate gratification, they argue that it is a lack of accurate mental accounting that leads to a decrease in predicted pain of paying. Using the credit card for the first purchase might still invoke enough negative feelings to experience the “whole” pain of paying for the purchase. The second, third, fourth. . . purchase might not invoke the same levels of pain in proportion to the money spent using the credit card. Gross and Souleles (2002) explain this phenomenon due to poor mental accounting. People are not able to correctly remember how much they have already spent. They also argue that this would also occur with multiple cash expenses, but to a lesser extent. Their explanation provides reasoning for why most individuals experience a nasty shock when they are presented with their credit card bill, as many cannot accurately recall all the individual expenditures.

There is also overlap in the predictions made by Zellermyer’s (1996) pain of paying and Soman’s (2003) theory of transparency. Both theories argue that the least transparent methods, with a strong emphasis on payment coupling, do inhibit spending the least. Both argue that this is due to an increased lack of salience. Little contemporary research has looked into this reduced salience beyond expenditures. Studies that have done so, found not only a clear relationship between salience of payment and expenditure, but also found a relationship between salience and the ability to correctly recall expenditures made. This evidence would support the findings by Gross and Souleles (2002) who argue that credit card users often fall into the trap of spending their money “twice”, due to not being able to correctly recall expenditures. We will look into this aspect next.

2.3 Expenditure Recall

One key feature throughout the effects of payment methods, and the theories explaining them, is the reduced salience of the transaction, and the reduced salience of the transaction in memory. In this section we are going to explicitly look into the relationship between payment methods reducing salience, the direct effects this can have on expenditure recall, and the indirect effects it may have on personal finance management.

2.3.1 Memory

Memory, like many of our cognitive resources, is limited in its capacity. Despite this, most people are able to recall a multitude of events that have happened to them. Events that can be recalled easiest and most accurately tend to have one thing in common: vivacity and salience (Strongman and Russell, 1986). Events that invoke strong emotional responses, positive or negative, are the ones that are turned into vivid memories. Even here we can make a distinction: research has found that events that invoke extremely negative emotions are more likely to be (accurately) remembered than those that invoke extremely positive emotions (Seidlitz and Diener, 1993). From this research we leap into the domain of different methods of payment. Linking memory to the pain of paying: as the pain of paying decreases due to lower levels of salience within a payment method, does the ability to correctly recall expenditures diminish as well?

Looking at research on payment methods and expenditure recall, we find that different payment methods do lead to different levels of accuracy in expenditure recall, which in turn leads to differences in willingness to pay and spending. Srivastava and Raghurir (2002) show a difference in the accuracy of expenditure recall when using different methods of payment, and their influence on future expenditures. They found that the more frequently cards were used for expenses, the less accurate the expenditure recall was and the larger the (positive) effect on future expenses was (Study 1). They also showed that a decomposition strategy, the dividing of the total expenditure into subcategories, made individual expenses more accessible to memory and was therefore effective in increasing the accuracy of recall. This effect was present in both cash, cheque and credit card, showing the largest change of accuracy in credit cards (Study 2). Chatterjee and Rose (2012) find results similar to those of Srivastava and Raghurir (2002). Looking at the effect of payment mechanisms on product perception, they found that consumers who had been primed with credit cards made more recall errors regarding the cost of different products they had just purchased within their laboratory experiment. In the second experiment, a word recognition task, participants were primed with either cash or credit card imagery.

The finding that the payment method is able to change product perceptions (in terms of cost and benefits) might link to the pain of paying. If less pain is expected within the purchase of a product, due to delayed payment (credit card), the product might be viewed more favourably. Whereas the purchasing of a product with cash would draw attention to its immediate costs, as those would occur immediately, triggering the pain of paying. However, this is mere speculation as no research has linked the theories, to our knowledge. Work by Soman (2001) looked at the ability of past expenses to influence future spending, with a prerequisite for this influence being the accurate recall of past expenses. Participants experienced four payment mechanisms and incurred expenses in four spending categories. Results showed that participants who paid for a series of past expenses by credit card were more likely to make an additional purchase than participants who paid for the same past expenses by cheque. Soman argued that this higher willingness for making an additional purchase was due to inaccurate recall of what had already been spent. This finding is in line with findings by Gross and Souleles (2002), who found that those who used credit cards underestimated their past expenditures and continued spending money as if they still had it, which they in fact did not. This work clearly establishes a relationship between payment method, the ability to correctly recall expenditures and the effect this has on future spending.

There is research contradicting the idea that payment methods influence expenditure recall. See-To and Ngai (2019) showed that there was no memory error differential when comparing three different methods of payment - cash, credit card and a stored value contactless smart card - when surveying consumers outside of six different grocery stores in a Hong Kong mall during a three-week period. The survey asked participants to estimate their spending, frequency of grocery shopping (per week) and method of payment. Other measurements of interest were payment timing (now compared to later), source of money (credit, current or cash) and the payment process itself. When comparing cash and direct bank account deductions as sources of money to credit as a source of money, no significant memory differential was found. When comparing the stored value contactless smart card as a payment process against cash, again no memory error differential was found. Even when comparing credit cards to cash as payment processes, there was no memory error differential found. These findings seem to contradict well established research findings on expenditure recall within credit cards (Prelec and Simester, 2001; Raghubir and Srivastava, 2008; Soman, 2003; Thomas, Desai, and Seenivasan, 2011; Tokunaga, 1993). However, this prior research tends to focus on multiple transactions, over a longer-term, whereas the study by See-To and Ngai (2019) focuses exclusively on single transactions that have just occurred. This could potentially explain the lack of a memory error differential, or more commonly known as decreased recall accuracy. This study did find,

however, that expenditures were highest when using credit cards, or any source of money that was able to postpone payment. Moreover, the amount spent was linked to the memory error. The higher the amount spend, the higher the error. The researchers explained this as a reduction in the pain of paying. The less accurate expenditure is being recalled, the less pain is felt during the shopping and the more a consumer is willing to buy and spend.

All of the theories above continue to ground themselves in the pain of paying. However, there has been evidence contradicting the existence of the pain of paying (Banker et al., 2017; Plassmann, Mazar, and Rangel, 2011). It is therefore plausible that the pain of paying is not the driving mechanism behind reduced recall accuracy, or any of the behaviours associated with payment methods. Rather, we should shift our focus towards the salience of a payment and its impact on recall. From a (short-term) memory perspective, the longer one is exposed to a stimulus, the easier it is to recall, and the more accurate the recall is likely to be (Magnussen et al., 1991). As payment methods have become more convenient, they have also become faster. Paying by PIN-verification is quicker than paying by cash, with contactless payment methods being the quickest. Due to the shortened duration of the transaction, it is unlikely that short-term memory will have sufficient time to encode the expenditure. As a result, it will be more difficult to retrieve this expenditure from memory, as it was never properly encoded. We would expect to find a difference in the ability to correctly recall the expenditure, but need not find a difference in the pain of paying experienced during the transaction. Another part of exposure is the visibility of the expenditure. Specifically in the case of contactless cards, visibility is reduced even further, as the tapping of the card obscures the amount to be paid. This also holds true for mobile devices also, as they can be classified as a subcategory of contactless payments. Due to the speed of the payment and the reduced exposure to the total to be paid, the payment is less salient in memory. It might be this reduced salience which leads to the behavioural outcomes established by prior evidence, and not the pain of paying. The memory account would be in line with findings by See-To and Ngai (2019), who find that expenditure recall is directly linked to willingness to pay, and that this relationship holds regardless of payment method used.

2.3.2 Awareness

When it comes to linking theories, there are other theories able to explain the increasingly inaccurate recall of prices. It has been argued that the usage of cash, due to its physical limitation, primes the consumer for increased price awareness. In that case, it is not transparency or pain that drives spending, but awareness. Thomas, Desai, and Seenivasan

(2011) tested for this and suggested that the painlessness of paying by credit card is not due to price neglect. In their second study, participants in the credit card condition did not experience more pain of paying for products, when paying explicit attention to the prices. This has been confirmed by a surprise recall task, in which all participants performed similarly, regardless of payment method condition. This result is important as it shows that the pain of paying is not dependent on price awareness. Consumers experience less pain when they use less vivid and less salient modes of payment, making them more likely to overspend, and this effect might not be able to be mitigated by paying closer attention to prices. This truly shows the importance of payment method on the purchasing process.

2.3.3 Mental and Real-time Accounting

Whether we subscribe to the memory or the awareness account of expenditure recall, we aim to find a mechanism showing that there is reduced accuracy in expenditure recall, influenced by payment method. The type of expenditure recall whereby an individual keeps track of their spending, possibly in different categories (e.g. bills, groceries, insurance, eating out) to determine how much more they can spend is known in the behavioural science literature as mental accounting (Thaler, 1999).

Mental accounting is the activity of keeping a running total, or separate totals if you are working with categories, in your head. It is not being tracked anywhere else (e.g. written down), it is all done mentally, as the name suggests. We have hinted at mental accounting before, as we have referred to research having shown that reduced salience of payments makes it more difficult to track expenses correctly mentally, leading to spending “twice” and increasingly incurring debt (Gross and Souleles, 2002). If we believe that different payment methods induce different levels of salience and that this affects memory, and as such accurate recall of previous expenditure, mental accounting must be made increasingly more difficult with the implementation of less salient payment methods. As such, mental accounting should become increasingly less accurate (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), leading to spending outside of the mental budget (Gross and Souleles, 2002; Thomas, Desai, and Seenivasan, 2011) and increasing the chances of incurring overdraft fees and debt (Garrett et al., 2014; Gross and Souleles, 2002; Meyll and Walter, 2019). Findings which are supported by prior research.

In addition to payment methods influencing the accurately keeping track of expenses and remaining resources available, research has also found preference reversals associated with shifts in mental accounting caused by the use of different methods of payment. Prelec

and Loewenstein (1998) found that preferences for payment coupling change depending on the good to be purchased. Consumers wanted to pre-pay for a holiday, but would postpone payments for a washer-dryer set of equal monetary value, showing that different mental accounts were triggered for the two expenses that can be categorised as transient and durable, respectively. This coupling is, as we have seen before, dependent on how close the payment is to the purchase of the good/service. Prelec and Loewenstein (1998) argue that coupling with credit cards is reduced temporally (Raghubir and Srivastava, 2008), but also cumulatively: the charge to be paid at the end of the month does not refer to a single item or transaction, but to several, no longer distinct transactions. Looking at credit card debt repayment, they argue that consumers will pay off expenditure on transient forms of consumption more quickly than expenditure on durables, because the pain of paying can be offset by the future anticipated pleasure of consumption only when money is spent on consumption that endures over time. Consistent with this prediction, Quispe-Torreblanca et al. (2019) found that repayment of debt incurred for nondurable goods is an absolute 10% more likely than repayment of debt incurred for durable goods. When people are able to pay by credit card, rather than pre-paying or post-paying consistently, they choose the level of payment coupling depending on the product category. Different products trigger different mental accounts.

The introduction of newer and more convenient payment methods is not the only development we have seen in the personal finance and fintech sphere. Mobile phones have more functions than just that of being a payment method. One of these functions is being a device to manage finances. Most individuals with a mobile phone practice online banking, and have their banking app, if not also a different financial management app (from hereon PFM tool), installed on their device. As such, the mobile device is both for paying and tracking payments. It is the first time in the history of payment methods that these two functions are merged.

From a mental accounting perspective this is ideal (Thaler, 1999). With a mobile device that tracks the expense as it is made, the need for mental accounting diminishes, as the opening of one’s banking app is enough to correctly update the amount of money spent, and the amount of money left, in one or even multiple (spending) accounts. Moreover, payments through mobile phone are by default linked to a payment app, which needs to be installed on the device, that sends out a notification once a payment is made. Initially used as a means of immediately detecting theft and fraud, this also aids in making recall of the expenditure easier, and aiding correctly updating the mental account.

However, research does not seem to support the mere existence of a spending overview to impact behaviour. Research by Huebner, Fleisch, and Ilic (2020) looks into using

the mobile device as a channel of personalised feedback interventions to reduce credit card spending. They show that increasing the salience of cashless payments through personalized feedback interventions helps people gain better control over their credit card spending. In addition, they use this app-based intervention to let people categorise their expenses as ordinary or exceptional, and split treatment groups into who gets feedback regarding which type of spend (none, ordinary, exceptional and both). They show that consumers require both an aggregated overview of all their spending, and feedback on both their ordinary and exceptional spending. The authors explicitly argue that the rehearsal of an individual transaction was not sufficient to nudge credit card users towards spending less. Instead, both the categorising of transactions and the aggregated feedback were necessary for participants to reduce their spending.

The idea that mere representation of how much has been spent and how much is left (the account balance) is enough to change behaviour has been rejected before. Aforementioned research by Huebner, Fleisch, and Ilic (2020) has shown this to be true, but research by Pocheptsova Ghosh and Huang (2020) shows that mere presentation of the bank account balance has a positive effect on spending, in the sense that it increases spending, and increases the likelihood of consumers who actively use these PFM tools to hit overdraft. This rather surprising result addresses the fact that more research needs to be done to understand how people interact with budgeting and financial tracker apps to their own benefit, or detriment.

2.3.4 Theoretical Contradictions

As outlined in the previous section on “Merging the Theories”, most theories have overlap in what they predict with regards to the effects of payment methods on personal finance. According to the pain of paying (Zellermayer, 1996), transparency (Soman, 2003), and multi-functionality (Gafeeva, Hoelzl, and Roschk, 2018), as payment methods become easier to use, due to their simplicity, speed, lack of verification, and constant availability of money, they reduce in salience. As it becomes easier to spend it also becomes easier to lose track of spending. This reduced salience should lead to increased spending, reduced spending awareness and generally worsened personal financial management. We call this the simplicity account.

With most payment methods the increase of simplicity and the reduction of salience have gone hand in hand. The latter following from the former. Cash is not simple to use at all, it is painful (Zellermayer, 1996), it is transparent (Soman, 2003), it is concurrent (Raghubir and Srivastava, 2008) and it only has one real function (Gafeeva, Hoelzl, and Roschk, 2018). This makes it an effective budgeting tool (Doyle et al., 2017), as spending

is inhibited, by both the factors outlined, as well as the limitations of the money available for use. Other methods of payment have become increasingly simpler in usage, which was seen as progress (Rosenberg, 2005). Payment cards, specifically credit cards, were introduced to make payments less of a hassle, with a higher availability of money: the increased safety of being able to access a lot of money without the risk of having to carry a lot of physical cash (Krol et al., 2016). The transactions became safer, but were also of higher volumes, quicker, non-concurrent (in the case of credit cards) and further removed from spending “real” money (James, 2017; Raghubir and Srivastava, 2008). Overall, the payment methods became easier (Angrisani, Foster, and Hitczenko, 2013) and as a result less salient (Soman, 2003; Zeller-mayer, 1996).

This is, however, not the case for all payment methods. Mobile payments, due to their multi-functionality, could possibly be exempt from this reduction in salience through simplicity. Theories grounded in mental accounting argue that mobile payments should be more salient, as the device itself tracks the payments, and provides users with direct feedback of their spending. The direct feedback comes in the form of a notification sent immediately after the spend has been made. This feature was initially a way for alerting consumers in case of theft and fraud, but can have mental accounting benefits. In addition to the notification sent to check whether the payment was made by the mobile device owner, the notification of spending can also provide more detailed information when users change the default settings of the app, as well as have continuous access to their online banking app via their mobile device, allowing them to see the total overview of their spending. As a result, spending should become more salient, leading to an increased awareness of spending and improved expenditure recall. It is possible that these effects also spill over into other aspects: as a decreased accuracy of spending has been associated with an increased willingness to continue spending (See-To and Ngai, 2019), it is possible to conceive that the reverse could hold true also. If accuracy of expenditure recall were to increase, would this lead to reduced spending, and generally improved personal financial management? If this is the case, this would provide a serious account against the simplicity account that houses theories such as the pain of paying. The idea of having a payment method which can both increase simplicity and salience at the same time is novel and as such there is little research to substantiate this claim. This thesis will aim in contributing to this body of evidence.

2.4 The Spending Distribution

With the constant access to money, via payment cards or mobile devices, we have seen a shift in how most expenses are made, and how they are tracked. People who have access to money, or simply have less of a limit on their spending, are more likely to impulse spend (Thomas, Desai, and Seenivasan, 2011). As such, they are more likely to buy morning coffees, eat lunch out, or take a more expensive Uber rather than wait for public transport. These impulse expenditures are often small, but they do add up. More importantly, they fill up a bank statement, both paper and online, with these smaller expenses, making it more difficult to identify the core items on the statement, such as salary, mortgage payments, etc., making it increasingly difficult to accurately keep track of expenditures mentally. This shift in moving individual smaller expenses away from cash and onto cards and bank statements was initiated by credit and debit cards, but was even further exacerbated by the introduction of contactless and mobile payment methods, making the process of payment faster and more convenient (Gafeeva, Hoelzl, and Roschk, 2018; James, 2017; MasterCard US, 2011; Trütsch, 2014).

However, it is entirely possible that the role of payment method, although well established, is an indirect, rather than a direct, cause of the results found. A large part of spending, and personal finance management as a result, relies on perception and memory of the resources already used, and those that are left. A large part of managing one's finances is accurately being able to track them, accurately memorising and estimating how much has already been spent, how much still has to be spent, and how much remains. From a memory perspective, payment methods in and of themselves might not be the leading cause in increased spending, decreased accuracy of expenditure recall and increased debt occurrence. It might be the spending distribution driving these effects, and how different payment methods change what this distribution looks like.

The shift in the spending distribution with the introduction of a new payment methods has been well corroborated. Research on credit card usage, as compared to cash usage, has been linked to increased spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Runnemark, Hedman, and Xiao, 2015; Soman, 2003; Tokunaga, 1993) and reduced impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011). Looking into contactless payments we see a similar picture, as contactless cards have been found to increase by 30% per-transaction with a contactless card (MasterCard US, 2011), but the average spend remained under \$25. Trütsch (2014) found that contactless cards, both debit and credit, resulted in higher spending at the point of sale compared to their non-contactless equivalents. The increases being 10% for credit, and 8% for debit cards. These relatively small changes do add up: they change both

the total of the distribution and the number of stimuli the spending distribution consists of. As impulse spends tend to be small in nature, the promotion of smaller expenditures by different payment methods is likely to lead to an increasingly more positively skewed spending distribution, a lower mean expenditure and increased standard deviation as well. Contactless expenditures do fit these characteristics: the average contactless spend being just under £10, in the UK (UK Cards Association, 2019), supporting the hypothesis that these payment methods skew the spending distribution towards becoming increasingly more positive.

2.4.1 Number of Transactions

Research does find there to be a role for the distribution of numbers, as seen with a spending distribution, on accuracy of recall and preference. Looking into recall again, we once more emphasize that memory has a finite capacity. It has been well established that within short-term memory, individuals can hold up to 7 ± 2 items (Miller, 1956). A very recent expenditure could make up one of these items, but if the expense is more complex in nature, £281.57 instead of the much easier to remember £300, it can qualify as a “chunk” of which people are able to hold 4 ± 1 in their working memory (Baddeley, 1994; Miller, 1956). Transitioning this to longer-term memory, rather than forgetting the event, would require repetition or a form of application; in this scenario the updating of the mental account balance, as seen with mental accounting (Thaler, 1985).

The level of difficulty is not the only aspect that influences the accuracy of recall and the effectiveness of retention. As mentioned before, short-term memory is a finite cognitive resource. When recent expenditures do not transition to longer-term memory, they fade out, become increasingly more difficult to recall (without direct prompts) and are forgotten. This process will make expenditure estimates, and the accurately updating of the mental account balance increasingly more difficult, and inaccurate. This can be influenced by the sheer quantity of expenses to be remembered. As the number of transactions goes up, there is more room for error, and increased difficulty to keep track of both expenses made and monetary resources left. In addition, as spending becomes more frequent, it becomes less salient. Short-term memory to longer-term memory transition favours novel and unpredicted (salient) events (Snyder, Blank, and Marsolek, 2008). Once something has become quite ordinary, common or often rehearsed, it loses salience, and is less likely to be committed to memory. Moreover, when moving more transactions to a singular place, such as a bank statement or an online banking app, the sheer volume of transactions might make it more difficult to get an accurate overview of the number of transactions, and the total spending they sum to. As a result, the sheer increase in

transactions can have an influence on the accuracy of perception and recall of expenditure. Interestingly, most payment methods, as compared to cash, have been linked to increases in the frequency of spending (James, 2017; MasterCard US, 2011; See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011; Trütsch, 2014).

2.4.2 Total Spending

In addition to the number of transactions, the main finding associated with novel payment methods has been increased spending (Feinberg, 1986; Hirschman, 1979; MasterCard US, 2011; Prelec and Simester, 2001; See-To and Ngai, 2019; Soman, 2003; Thomas, Desai, and Seenivasan, 2011; Tokunaga, 1993; Trütsch, 2014). Most of these payment methods have also been linked to higher debt occurrence (Gross and Souleles, 2002; Meyll and Walter, 2019), indicating that the accuracy of memory needed for correct mental accounting might be reduced. Accuracy of spending recall also influences future spending (See-To and Ngai, 2019). As such, there might be a direct link between increased spending, reduced memory and debt occurrence. It is entirely possible that recall error increases as a result of the number of transactions increasing, but it may also simply do so as a function of the total spend: if people are always within a 10% margin of being within their actual expenditure when estimating, than absolute estimation error will increase as actual spending increases.

In addition to these findings, research specifically looking at expenditure recall in grocery stores found that customers were systematically underestimating the total value of their shopping baskets (Van Ittersum, Pennings, and Wansink, 2010). This finding is also corroborated by Scheibehenne (2019), who tested 40 participants in a lab, displaying sequences of 24 numbers, with varying totals and underlying distributions. He found a general tendency towards underestimation of the total of the sequences, with no effect of the underlying distribution characteristics such as modality, skew and kurtosis. Additionally, Scheibehenne (2019) conducted a study in which customers of a grocery store were asked to estimate the total of their shopping basket (in CHF) before checking out. Again, he found a tendency towards underestimation, regardless of the characteristics of the underlying distribution. He also found that this bias increased for larger sums, in line with our predictions and previous findings of similar patterns of underestimation with respect to the perception of numerals in general (Dehaene, 2011) and in a consumer context in particular (Van Ittersum, Pennings, and Wansink, 2010).

In addition to Scheibehenne (2019) finding an effect of total but not of the underlying distribution, he also found that underestimation did not depend on the underlying frequency distribution, a finding which holds for both studies. This goes against previous empirical and theoretical support. However, there is previous research that also did not

find such a relationship when information was presented sequentially (Hutchinson, Wilke, and Todd, 2008). Overall, this research does point at a clear relationship between the total value of a distribution and the error of estimating its total.

2.4.3 Standard Deviation

The use of newer payment methods has been shown to lead to different spending patterns, giving way to smaller, impulse spends (Thomas, Desai, and Seenivasan, 2011). This does not merely affect the spending distribution by lowering the average-per-item-spend and adding more items to the distribution, it also increased the standard deviation of the distribution. The lower bound is being moved further down, towards zero, assuming that most impulse spends are small in nature (e.g. an additional coffee to-go) rather than large spends at the top of one's disposable income, which research does bare out (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011; UK Cards Association, 2019). By also reducing the average-per-item spend, it is possible that the increased standard deviation of the spending distribution changes the way the true mean, or the true total of the distribution are perceived. In the case of increasingly using methods such as contactless, and the presumed adding of smaller expenditures to the original spending distribution, we expect the perceived mean and total to be lower than the true mean and total.

Research by Brusovansky, Vanunu, and Usher (2019) shows that the perception of the mean of a distribution changes how people judge that distribution; favourably or not. In their experiment, participants were presented with rapid numerical sequences representing performances, class feedback, or rewards, to rate the Hall of Fame eligibility of basketball players, or their liking of athletes, lecturers or slot-machines. Brusovansky, Vanunu, and Usher (2019) tested for the applicability of several models such as averaging, summation and the Peak-End heuristic, but found that averaging type models accounted best for participants' preferences. This finding supports the argument that a change in distribution, whereby the mean, and as a result the standard deviation, are changed will have an effect on peoples' perception of the distribution, and their estimated value of said distribution.

2.4.4 Skew

In addition to the standard deviation changing, the skew of a spending distribution also shifts when customers favouring newer payment methods alter their spending to include smaller, impulse spends (Thomas, Desai, and Seenivasan, 2011). A distribution in which small expenditures occur most frequently, or at least more frequently, with few larger

expenditures is referred to as a positively skewed distribution. In this type of distribution the median is smaller than the mean. As the median lies at the midpoint of a frequency distribution of observed values or quantities, in this case expenses, it is likely that people will judge this as the mean, underestimate the mean, and potentially underestimate the total value of the distribution. With regards to spending, this means underestimation of the total spending, leading to worsened financial management in the form of hitting overdraft or incurring debt. Moreover, due to the sheer volume of small, potentially not salient expenditures (Soman, 2003; Zellermyer, 1996), it is likely that people forget some expenditures, even further fuelling the underestimation of their total expenditure.

In contrast to the positively skewed distribution described above stands the negatively skewed distribution. This is a distribution in which larger expenditures occur most frequently, with fewer small expenditures occurring. In this type of distribution the median is larger than the mean. As the median reflects the expenditure seen most often, it is likely that people will judge this as the mean, and overestimate the mean, and potentially overestimate the total value of the distribution. With regards to spending, this means they overestimate total spending. Moreover, due to the sheer volume of larger expenditures, which are judged as being more salient, it is likely that people are quite aware of their expenditures. This can further fuel the overestimation of their total expenditure, or undo some of the initial overestimating. Regardless, as contrasted to those experiencing the positively skewed distribution, those with negatively skewed distributions of spending either quite accurately estimate their spending or overestimate the total of their spending. As a result, they are less likely to get into forms of debt associated with spending beyond one's means.

It is assumed that most people experience positively skewed distributions rather than negatively skewed distributions. Most have several larger expenses such as rent, mortgage, healthcare, insurance, vehicle maintenance or education fees, often on a monthly basis. More frequently occurring are grocery shops and eating out, which are often smaller expenditures. From there, the most frequent occurring expenditures are much smaller, such as the aforementioned morning coffees and lunches-to-go. With constant access to money, it is very easy to spend a couple of pounds per day.

Research by Raghubir and Srivastava (2009), as outlined in the section on expenditure recall, examined whether there are systematic differences in memory traces across different denominations, and whether these are related to differences in likelihood of spending as a function of errors in the estimation of the contents of one's wallet. This relates to skew as they tested for the effect of having smaller denominations, and having increasingly larger amounts of smaller denominations, effectively skewing the value distribution of the money in the wallet of the participant. Raghubir and Srivastava showed that having more

smaller denominations made it more difficult to accurately keep track of money currently in possession and that participants with increasingly more smaller denominations in their wallets were not only less accurate in their estimations, but systematically underestimated the value of their wallet. The effect of underestimation was especially strong if both the skew was positive, and the number of units in the wallet were greater. This is in line with theories on short-term memory recall, where accuracy of recall is dependent on the quantity to be recalled (Baddeley, 1994). Lastly, they established that the estimation errors are greater for smaller denominations.

Research on the effect of skew in different contexts, in this case wage payment distributions, showed that participants of the wage payment distribution task had a clear preference for receiving a set of negatively skewed wage payments, rather than a set of positively skewed wage payments, despite the mean and total value of these payments being the same (Tripp and Brown, 2016). The authors explain this by emphasizing that in a negatively skewed distribution the larger values (as relative to the other values in the same distribution) are seen more often and as such might influence the participants' perception of the total value of the distribution. However, they did not test for the actual perception of the distribution so this remains conjecture. This study was a replication of Parducci (1968) who also found that the average satisfaction with individual payments was higher for negatively skewed sequences.

Estimation accuracy for a sequence of numbers may also depend on the shape of the underlying frequency distribution. Experimental evidence from research on risky choices indicates that preferences critically depend on the distribution of values that people experienced in the past (Stewart, 2009). Likewise, grocery shoppers can be influenced by the skew of product prices over time (Niedrich et al., 2009). Such patterns can be explained by several theoretical accounts including the decision by sampling theory (Stewart, 2009) and the range–frequency model (Parducci, 1965), and they align with early research on perception showing that negatively skewed distributions lead to lower mean estimates compared to positively skewed distributions (Parducci, Thaler, and Anderson, 1968).

2.5 Summary

Research finds a clear effect of payment method on spending, spending recall, and to some extent, debt accumulation and other measures of personal financial management. However, most of this research has focused on the disparity between cash and credit card. Relatively little research has been done on the effect of debit cards, contactless cards and mobile payments and their effects on various aspects of personal finance management.

Looking at credit card research there is robust evidence establishing an association between this payment method and increased spending, more frequent spending, reduced accuracy of expenditure recall, impulse spending and debt accumulation. Some of these findings have also been associated with contactless payment methods (increased spending and frequency of spending) and mobile payments (increased debt accumulation).

Several frameworks and theories have been designed to explain why payment methods differ from each other. Using Zellermyer’s pain of paying, Soman’s transparency framework or Raghurir and Srivastava’s payment (de)coupling, we can rank payment methods in terms of pain, transparency or tightness of coupling. This ranking indicates the level of deviation from cash, which is the default level of comparison, and the most painful, transparent and tightly coupled method of payment, due to its physical form, value representation and concurrency. There are slight differences between how the theories rank different payment methods, but the general overlap between theories proposes that credit cards are the most deviant from cash, and that debit cards fall somewhere in between the two.

Expenditure recall, an important facet of accurately keeping track of one’s expenses and remaining resources (mental accounting), can be influenced by the salience of a transaction. The more salient a transaction is, the more likely it is to be locked into short-term memory and transition into long(er)-term memory. It has been hypothesized that the increased (frequency of) spending associated with newer payment methods is due to lower salience of these transactions and spending money “twice” as the previous spend has been forgotten. If this is true, newer, less salient payment methods would lead to increased spending and higher debt accumulation. However, this could potentially be offset by the use of PFM tools, which support mental accounting by tracking expenditures and remaining resources in real-time.

In addition to a direct effect of payment method on expenditure recall and personal finance management, there may also be an indirect effect, mediated by the changes in the spending distribution. As mentioned before, there is a strong association between the method of payment and increased spending, increasing the total of the distribution. The total of the distribution has been found to predict the level of estimation error, with a clear systematic tendency for underestimation. A link has also been established between payment method and the frequency of spending; newer payment methods leading to more frequent spending. The frequency of the distribution has been associated with increased complexity and difficulty in accurate recalling or estimating the total and mean of a distribution. The impulse spending associated with newer payment methods leads to a larger standard deviation and an increasingly positive skew. The former has been

associated with underestimation through the reduction of the perceived mean of the distribution. The latter has been associated with reduced preferences for such a distribution, most likely caused by an underestimation of the mean and total of the distribution. Research has not yet linked the effect of payment methods on the spending distribution with personal finance management.

Chapter 3

The Effect of Contactless Payments on Expenditure Recall

3.1 Introduction

This paper investigates the effect of contactless payment methods on the accuracy of expenditure recall from single transactions. Contactless payment involves paying by tapping a payment card or other device on a payment machine, without typing a Personal Identification Number (PIN). Since their introduction in the early 2000s, these methods have gained increasing popularity across the globe, now representing the majority of in-store transactions in the UK, the Eurozone and Australia (Campbell, 2015; Statista, 2020b; WestPac, 2017), a trend greatly accelerated by the physical distancing measures deployed during the Covid-19 pandemic (Financial Conduct Authority, 2021; Statista, 2020c).

As with the global proliferation of payment cards, the increased uptake of contactless payment methods and the resulting replacement of cash may not be universally beneficial (Rosenberg, 2005). Cash is often used as a budgeting tool or for constraining expenditure (Doyle et al., 2017), activities that may become harder with contactless payment. In the next subsection, we review the evidence on the effects of payment methods. We then turn to the mechanisms that have been proposed to explain those effects and to the motivation of our studies.

3.1.1 Evidence

Although standard economics suggests that, in the absence of frictions such as liquidity constraints, payment methods should not have systematic effects on spending behaviour,

prior research suggests that they do. Several studies have compared credit cards and cash, and found credit cards to be associated with increased willingness-to-pay and increased spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Soman, 2003; Tokunaga, 1993), less accurate expenditure recall (Gross and Souleles, 2002; Raghurir and Srivastava, 2008; Srivastava and Raghurir, 2002), reduced impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011) and debt accumulation (Gross and Souleles, 2002). It has also been found that those who pay by credit card feel less attached to the products they buy (Shah et al., 2016), and that the expected use of credit cards for the purchase of a product is associated with increased focus on the product’s benefits, rather than its cost (Chatterjee and Rose, 2012). Similar effects have been found comparing cash and debit cards, with significantly higher willingness-to-pay with debit cards, even after controlling for cash-on-hand constraints, spending type, price familiarity and consumption habits (Runnemark, Hedman, and Xiao, 2015).

By comparison, research on contactless payments is still in its infancy, but the few studies that have been done do show alignment with earlier research on credit cards. MasterCard US (2011) found that per-transaction expenditure increased by 30% with their PayPass contactless cards, but offered no explanation for this increase. Trütsch (2014) showed that contactless cards were associated with higher spending at the point of sale compared to their non-contactless equivalents.

In a study by James (2017), a sample of British students reported increased spending, reduced awareness of spending and feeling less in control of their finances when using contactless payments. Many students reported that they did not feel like they were spending “real” money when using contactless payment methods.

Regardless of payment method used, See-To and Ngai (2019) found that less accurate expenditure recall was associated with increased willingness to spend. As recall accuracy was higher for cash and lower for other payment methods, this suggests that willingness to spend may be higher for card payment methods. For this reason, we focus on expenditure recall as our primary dependent variable.

3.1.2 Theories

The effects of payment methods documented in the literature have been linked to factors such as the so-called *pain of paying*, differences in the methods’ levels of *transparency* and the *decoupling* between consumption and payment that is introduced by methods such as credit cards.

The pain of paying is the label that Zellermyer (1996) used to refer to the negative feelings caused by spending money. These feelings depend on how well the payment method reflects value, the physicality of the transaction, and the temporal proximity between the payment and the money outlay. On this account, cash is the most painful method, because it very clearly reflects value (through banknotes and coins), it results in very physical transactions as it is counted and manually handed in, and it immediately results in a reduction of the payer's monetary resources. Credit cards, on the other hand, do not reflect value, are often not used in a way that prominently emphasizes how much is being spent, and often result in deductions from one's account weeks if not months after the relevant transaction. Hence, the pain of paying associated with credit cards may be much lower than for cash. To avoid the associated negative feelings, people may be less inclined to spend money with cash than with credit cards.

The pain of paying may also explain differences in expenditure recall. Events that invoke a strong emotional response are turned into vivid memories (Strongman and Russell, 1986). Events that result in negative emotions are more likely to be (accurately) remembered than those that cause positive emotions (Baumeister et al., 2001; Seidlitz and Diener, 1993). It is plausible then that payments made with methods that induce more pain of paying are recalled more accurately.

Soman (2003) attributed the effects of different payment methods to their different levels of transparency. A method is more transparent the more it allows the user to keep track of how much is spent and how much is left to spend. Cash is more transparent than credit cards, hence resulting in more accurate recall and more effective budgeting.

The idea of decoupling also focuses on the concurrency, or otherwise, between a transaction and the resulting money outlay (Srivastava and Raghurir, 2002). The emphasis is on the salience of the resulting benefits and costs. For someone who pays by cash, the payment is more easily juxtaposed to the benefits of consumption, whereas someone who pays by credit card will enjoy the benefits of consumption whilst the cost of post-payment will be distant in the future. By reducing the salience of the money outlay, post-payment may make people less likely to pay attention to how much they are paying, hence less likely to recall the expenditure and more willing to spend.

There are reasons to think that these mechanisms will also be in operation, possibly to a greater extent, with contactless payments. Contactless methods make the transaction quicker and simpler than with payment cards (e.g., by not requiring a PIN), and this may reduce the pain of paying even further. Arguably, contactless payments are no less transparent than other cards on which the contactless function is activated, although it is possible that the additional contactless feature of a payment card may reduce the salience of the payment even further. As the possibility to make contactless payments is often just

a feature of a credit or debit card, contactless should not affect the strength of decoupling associated with the card.

The pain of paying is the leading explanation of the effects of payment methods. Evidence compatible with it has been found in surveys (e.g. Zellermyer, 1996), experiments (e.g. Chatterjee and Rose, 2012) and neuroscientific studies (e.g. Knutson et al, 2007). Survey measures come in the form of directly asking participants to rate the pain of paying as they are going through a transaction or shortly afterwards. Experiments have found a difference in self-reported pain of paying following manipulations involving the presence of credit card logos (Chatterjee and Rose, 2012), sentence unscrambling tasks (Plassmann, Mazar, and Rangel, 2011), or recalling past expenditures (Srivastava and Raghuram, 2002). The pain of pain has been linked to increased activation of the insular cortex – typically associated with experiencing physical pain – found in fMRI studies of online shopping tasks (Knutson et al., 2007). The degree of activation has been found to differ between individuals, with some (“tightwads”) experiencing more pain, and others (“spendthrifts”) experiencing less (Rick, Cryder, and Loewenstein, 2008).

More recent neuroscientific evidence questions the role of the pain of paying. Plassmann, Mazar, and Rangel (2011) found increased insular activity when participants were exposed to electric shocks, but not when they had to pay for an item they just won at an auction. Banker et al. (2017) found that shopping with credit cards did not result in lower insular activity relative to cash, but generally facilitated greater reward sensitivity, rendering consumers less sensitive to price information.

This suggests another potential mechanism for the effects of payment methods. When price loses salience, price and total amount spent become harder to encode in short-term memory, regardless of temporal distance. This reduced price sensitivity may work for all payment methods that increase convenience, including contactless. From a short-term memory perspective, a stimulus is easier to recall accurately the longer one is exposed to it (Magnussen et al., 1991). The speed of contactless payments reduces exposure to the total to be paid. This is also because the “tap” motion of the contactless card on the payment terminal may cover the screen of the terminal. There will be less time for the expenditure to be encoded in short-term memory, making it harder to retrieve it. According to this account, differences in recall accuracy may be a memory-driven phenomenon unrelated to the pain of paying.

3.1.3 Motivation

We conducted two pre-registered studies to establish the relationship between contactless payments and expenditure recall. Study 1 was an observational study conducted as a proof

of concept, to establish whether contactless is indeed associated with worse expenditure recall. Having found evidence that this is the case, in Study 2 we randomly allocated people to payment methods to measure a possible causal link between contactless and expenditure recall. We also included pain of paying measures to investigate this as a possible mechanism.

Both studies restricted the analysis of expenditure recall to individual transactions. This has the advantage of greatly simplifying the study design, while still providing valuable insights about personal finance management. Inaccurate expenditure recall may increase the willingness to spend and lead consumers to spend more than they initially budgeted for, or than they can afford. Worsened expenditure recall has been shown to adversely impact consumers' ability to manage their spending and personal finances (e.g., Gross and Souleles, 2002; Raghubir and Srivastava, 2009; See-To and Ngai, 2019). On a singular transaction level, these effects may be small. However, the inability to correctly recall a single expenditure may carry over into reduced expenditure recall for multiple expenditures. This may worsen longer-term expenditure recall and the ability to accurately keep track of one's expenses or manage one's finances, as seen with credit cards. If the ease of contactless payments increases the number of transactions individuals make, the combined effect of worse recall may potentially be even larger.

3.2 Study 1

3.2.1 Method

Sampling

The study was conducted between 10am on Tuesday the 21st of November 2017 and 7pm on Monday the 27th of November 2017 at the Rootes Grocery Store on the University of Warwick campus (UK). Data collection stopped in the hour a sample size of 3000 was reached, as pre-registered. The questionnaire took on average about 2 minutes to complete.

Participants

A total of 3,022 individuals (56.5% female, mean age = 21.4, age range 12-83), of which 94% were students, completed the survey.

Procedure

Customers were approached by a research assistant as they were leaving the check-out area of the store. Each customer was asked if they would like to fill in a short survey and give up their receipt in exchange for a snack. If the customer accepted, they were asked to give their receipt to the research assistant, who ensured that the customer did not glance at it by explicitly telling them not to do so when handing it over. Customers who looked at their receipt were automatically disqualified from participation (this happened in just 28 cases). After handing the receipt to the assistant without looking, the customer was given the survey. Customers were asked their age, gender, and student status. They were then asked whether they had come through a standard or a self-service checkout, and which method of payment they had used between cash, PIN-verified credit card, PIN-verified debit card, contactless credit card, contactless debit card, contactless mobile device or student card (the student card is a pre-paid card without PIN-verification that, at the time of the study, could be used for transactions in the majority of campus outlets). Last, the customer was asked to recall the exact amount, in pounds and pence, spent on their purchase. After handing back the survey to the research assistant, the customer was offered the choice between a fruit or a chocolate bar. The survey and receipt were bound together by the research assistant.

Measures

Of primary interest are the method of payment, actual expenditure, and the recall error. The method of payment was taken from the receipt. The self-reported payment method (survey) agreed with the participant's report in 3,019 out of 3,022 cases). The actual expenditure was also taken from the receipt. The recall error was computed as the recalled expenditure response from the survey minus the actual expenditure from the receipt. In addition, the number of items purchased and the purchase time were taken from the receipt to function as covariates.

3.2.2 Results

Of the 3,022 responses, 17 had to be discarded because the answers were incomplete, the receipts were not matched correctly, or the answers were unusable (e.g., "I did not pay, I robbed the store"). We also discarded all 81 transactions made using the student card, because this payment method, being pre-paid and not PIN-verified, did not fit the contactless/non-contactless distinction. Last, we discarded any non-contactless transactions that were over £30, as the limit for contactless payments in the UK was £30 at the

time of the study. There were only two such transactions made with PIN-verified debit cards. The analysis was conducted on the remaining 2,924 responses. A summary of some key variables is presented in Table 3.1.

	Cash	Contactless Credit	Contactless Debit	Contactless Mobile	PIN Credit	PIN Debit
Amount Spent (£)	3.13	3.83	3.59	3.60	5.16	3.86
Estimate of Spending (£)	3.16	3.80	3.58	3.60	5.18	3.87
Recall Error Signed (£)	0.025	-0.035	-0.010	0.002	0.023	0.015
Probability of Correct Recall	0.71	0.60	0.64	0.63	0.46	0.63
Number of Items	2.23	2.59	2.38	2.59	3.24	2.53

Table 3.1: Mean of key variables per payment method in Study 1. Amount spent, its estimate and recall error are measured in GBP. The probability of correct recall is measured as a dummy variable with 0 indicating the participant was incorrect in recalling their expenditure. The number of items is a count variable.

In our pre-registration (<https://osf.io/7qjhw/>), we stated that we would compare the effects of cash, PIN-verified, and contactless payments on expenditure recall. We planned to analyse signed recall error and its absolute value as dependent variables. However, we found that 64% of people correctly reported their expenditure, and when expenditures were incorrectly recalled they were typically wrong by only a few pence. For this reason, our analysis of recall accuracy uses a binary variable indicating whether the expenditure was correctly recalled or not. We also planned to model the recall errors and their dispersion in a Gaussian dispersion regression model. However, modelling correctness captures the dispersion of recall error with almost no loss of information because, to a good approximation, people are either correct or wrong by at most a few tens of pence. This means that we are able to use a simple linear probability model with a dummy for correct or not as the dependent variable. Linear probability models have the advantage of producing coefficients that can easily be interpreted as marginal effects, and are typically accurate when estimated probabilities are not too close to 0 or 1. Our results are qualitatively and quantitatively similar to those of a logistic regression (see Appendix 3A).

Table 3.2 shows the estimated coefficients from a linear probability model, regressing correct recall against payment method, number of items purchased, point of sale type, time of day, and day of week. Estimates from this model are shown in Figure 3.1. The left panel of the figure shows the estimated marginal mean effect of payment method on the probability of correct recall, with the number of items in the basket, point of sale, day, and time held constant (averaging over the levels of these covariates).

	<i>Dependent variable:</i>
	Probability Correct
PIN-verified Credit Card	−0.173*** (−0.273, −0.074)
PIN-verified Debit Card	−0.063 (−0.128, 0.001)
Contactless Credit Card	−0.084 (−0.171, 0.003)
Contactless Debit Card	−0.061 (−0.123, 0.0004)
Contactless Mobile	−0.052 (−0.129, 0.026)
Number of Items (2)	−0.261*** (−0.302, −0.220)
Number of Items (3)	−0.318*** (−0.367, −0.270)
Number of Items (4)	−0.342*** (−0.409, −0.275)
Number of Items (≥ 5)	−0.482*** (−0.539, −0.426)
Point of Sale	−0.024 (−0.074, 0.025)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	2,922
R ²	0.140
Adjusted R ²	0.134
Residual Std. Error	0.447 (df = 2901)
F Statistic	23.535*** (df = 20; 2901)
Reference level payment method	Cash
Reference level number of items	1
Reference level point of sale	Cashier

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 3.2: A linear probability model of the probability of correct recall representing the results of Study 1.

To estimate the effects of contactless payment methods, we consider the following contrasts (a) an average effect of both contactless and PIN-verified debit cards versus cash, (b) PIN-verified debit card versus cash, (c) contactless debit card versus PIN-verified debit card, (d) contactless debit cards versus cash, (e) an average effect of both contactless and PIN-verified credit cards versus cash, (f) contactless credit card versus PIN-verified credit card and lastly (g) all contactless methods versus cash. These contrasts are shown on the right panel of Figure 3.1, where positive values indicate higher accuracy in expenditure recall with the first method than with the comparator.

When comparing debit cards and cash, we find that the estimated probability of recalling expenditure correctly is 6.2% (95% CI [0.2%, 12.2%]) higher with cash (see contrast (a)). When comparing PIN-verified debit cards to cash, we find that the estimated probability of recalling expenditure correctly is 6.4% (95% CI [0.1%, 12.8%]) higher with cash (see contrast (b)). When comparing contactless and PIN-verified debit cards, we find that the estimated probability of recalling expenditure correctly is 0.2% (95% CI [-4.0%, 4.4%]) higher with contactless for debit cards (see contrast (c)). When comparing contactless debit cards to cash, we find that the estimated probability of recalling expenditure correctly is 6.1% (95% CI [0.0%, 12.3%]) higher with cash (see contrast (d)). When comparing credit cards and cash, we find that the estimated probability of recalling expenditure correctly is 12.9% (95% CI [5.3%, 20.5%]) higher with cash (see contrast (e)). When comparing contactless and PIN-verified credit cards, we find that the estimated probability of recalling expenditure correctly is 8.9% (95% CI [-2.0%, 19.9%]) higher with PIN-verified for credit cards (see contrast (f)). The overall effect of contactless compared to cash is negative, with people being 6.6% (95% CI [0.3%, 13.0%]) worse at recalling their expenditure correctly (see contrast (g)).

For comparison we also consider the effect of the number of items purchased, which is the best predictor of expenditure recall. The coefficients in Table 3.2 show that recall accuracy drops as the number of items increases, with the largest drop from 1 to 2 items. Purchases of 5 items or more occurred relatively rarely, and as such were grouped together. An alternative coding for number of items, single vs. multi-item, reveals that expenditure from single-item transactions is 32.3% (95% CI [28.9%, 35.7%]), more likely to be recalled correctly (see Appendix 3C).

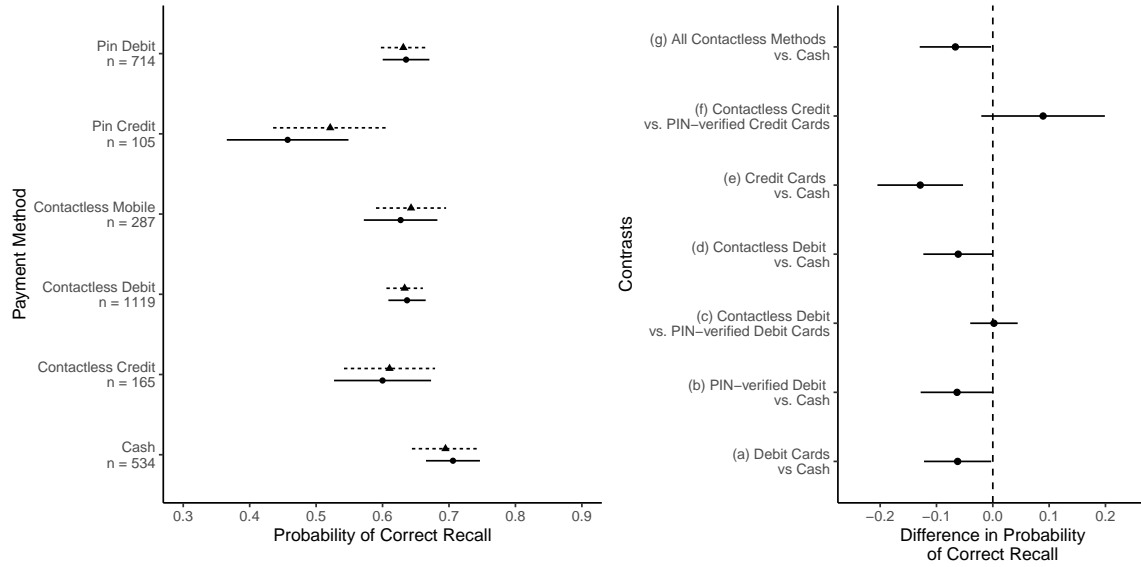


Figure 3.1: Results of Study 1. The solid lines with the circular markers in the left panel show the marginal effect of payment method and its confidence intervals, derived from the linear probability model of correct recall. Estimations were averaged over levels for factor variables, weighting levels by their frequency in the data. The dashed intervals with triangles show the effect of payment method without covariates. The right panel shows the pre-registered contrasts for Study 1. Error bars are 95% confidence intervals.

3.3 Study 2

Study 1 reveals an association between contactless payment and recall accuracy. To further investigate this effect, establish causality and further explore the possible mechanism behind this effect, we conducted an additional study.

In Study 2, we recruited participants from Prolific, to have access to a population with more varied demographics and shopping habits than the campus population of Study 1. Crucially, we randomly assigned participants to one of three payment method conditions (cash, PIN-verified debit and contactless debit card, the three most common methods in Study 1), to remove the possible endogeneity arising from participants self-selecting into using specific payment methods. To explore the mechanism through which payment methods affect recall, we measured the pain of paying and asked participants to complete the spendthrift-tightwad scale (STS), as the STS has been used to explain why some people (tightwads) experience more pain when paying than others (spendthrifts) (Rick, Cryder, and Loewenstein, 2008). Study 2 also differed from Study 1 in terms of the temporal distance between the shopping event and the expenditure recall. In Study 1, participants filled in the survey immediately after their shop. In Study 2, they had access to the link to a survey they could complete in the days after their shop. As a result, the time difference in Study 2 is much larger (on average 19 hours) as compared to Study 1.

3.3.1 Method

Sampling

Participants were recruited through Prolific. Our sample was restricted to residents of the United Kingdom, as our first study was also exclusively with UK-based participants. Data collection stopped as a result of funding having run out whilst having obtained a minimum of 1500 participants who completed part 3 of the survey, as pre-registered.

Participants

We initially recruited a total of 3,500 individuals, of which 2,017 completed the whole study. After several exclusions described below, 1,089 participants entered the analysis stage. We conducted several balance tests revealing that these exclusions did not change the characteristics of our sample.

Procedure

The study involved three parts. In part 1, participants signed up for a short online study on Prolific and were randomly assigned to a payment method (contactless debit card, PIN-verified debit card, cash). They were asked to use this payment method during their next grocery shop, which constitutes part 2. This grocery shop is a shop the participant would do anyway with no further restrictions or requirement; the participant could determine the store and time. We explicitly asked participants to collect the receipt from their shop and keep it for part 3 of the study. Participants were paid £0.15 for completing part 1, which lasted 2 minutes on average.

Participants who completed part 1 were invited to part 3 of this study, which they were asked to complete after their grocery shop. Part 3 of the study was a survey about the participant's shopping experience. They were asked what store they went to, whether this was their normal store, whether they felt the store offered them good prices, which payment method they were allocated in part 1, which method they used in the store, how painful they experienced the payment process to be, and how much they recalled having spent (without looking at their receipt); the survey also asked participants about their financial situation: their monthly income, their average grocery spend and whether they thought they were on a tight budget. After having answered these questions, participants were asked to upload their receipt (on a separate page). We used the receipt to see how

accurate their estimate of expenditure was, but also to see if they used the assigned payment method. At the end of this survey, which lasted on average 7 minutes, participants were paid £1.15 for their participation. Participation in all three parts paid £1.30.

Measures

The receipt recorded the actual expenditure of the participant and the method of payment (which agreed with the participant’s report in 88% cases). Of primary interest are the method of payment, the actual expenditure (taken from the receipt) and the accuracy of recall (a binary variable indicating whether or not the participant correctly recalled their grocery spend). Another variable of interest, predominantly as a mediator, was the pain of paying, measured on a scale ranging from -5 (extremely painful) and +5 (extremely pleasurable) (Rick, Cryder, and Loewenstein, 2008; Zellermayer, 1996). In our analysis, the pain of paying measure was normalised to a 0-1 scale, with 1 indicating the highest level of pain. The list of covariates also includes: income, monthly spending on groceries, being on a budget (yes/no), the STS, number of items purchased, point of sale (cashier/self-check-out), day of the week, time of the day, as well as the time difference between the grocery shop itself and the filling in of the survey. We also controlled for whether the participant was first asked to recall their spending and then estimate their pain of paying, or the other way round. These covariates can be found in Table 3.3 and in our pre-registration (<https://osf.io/j3e7t>).

3.3.2 Results

We had 2,017 submissions for part 3 of the study. Following our pre-registered exclusion criteria, we excluded all participants who indicated in part 3 that they did not wish to participate, leaving us with 1,927 participants. We excluded all participants who did not complete the survey in full, leaving us with 1,561 participants. We excluded participants who had used a different method of payment than the one allocated in part 1, leaving 1,380 participants. We removed participants who indicated looking at their receipt before estimating their grocery spend, further reducing our sample to 1,356. Additionally, we had to code the content of the receipts manually, and further excluded every participant who did not upload an image of the actual receipt or the image was of such low quality that it could not be read, leaving us with 1,257 participants. Last, the decision was made to exclude all spends above £45, as that was the spending limit on contactless cards in the UK at the time of the study, leaving us with 1,089 participants. Of the 1,089 participants, 527 are in the contactless condition, 227 are in the PIN-verified condition and 335 are in

the cash condition.

In our pre-registration, we stated that we would compare the effects of cash, PIN-verified debit, and contactless debit payments on accuracy of expenditure recall. Table 3.3 shows the summary statistics for each of the payment methods to put into context the results from Table 3.4.

	Cash	Contactless Debit Card	PIN-verified Debit Card
Amount Spent (£)	13.71	17.43	15.51
Estimate of Spending (£)	13.90	19.35	16.77
Recall Error Signed (£)	0.18	1.92	1.26
Probability of Correct Recall	0.15	0.07	0.11
Pain of Paying	0.40	0.38	.40
Spendthrift-Tightwad Scale	4.69	4.84	4.82
Annual Income (£)	25,746	26,746	25,132
Monthly Grocery Spending (£)	339	345	347
Being on a Budget	0.59	0.55	0.59
Number of Items	10.56	12.99	11.46
Time Difference	0.67	0.89	0.81

Table 3.3: Mean of key variables per payment method in Study 2. Amount spent, estimate of spending, recall error signed, annual income and monthly grocery spending are all measured in GBP. The probability of correct recall is measured as a dummy variable with 0 indicating the participant was incorrect in recalling their expenditure. The pain of paying is measured from 0 to 1, 1 being the most painful. The Spendthrift-Tightwad Scale is a scale consisting of multiple measures, indicating how easy it is for participants to spend money, and ranges from -3 to 15. Being on a budget is a dummy variable with 0 meaning the participant is not on a budget. The number of items is a count variable. The time difference is the number of days between the time the participant went shopping and the time they filled in the part 3 survey.

Table 3.4 shows the coefficients from a linear probability model, regressing a correct recall dummy on payment method, and covariates described earlier. We did not include actual spending as a covariate, as it was highly collinear with the number of items purchased ($r=.8$). Estimates from this model are shown in Figure 3.2. The left panel of the figure shows the estimated marginal mean effect of payment method on the probability of correct recall, both in the model with only payment method as the regressor (dotted line) as well as the model with all the covariates (solid line).

From Table 3.4 we find that the usage of contactless debit cards is associated with a significant decrease in the probability of correct recall when compared to cash. PIN-verified debit cards are also associated with a slight decrease in the probability of correct

recall, but this change is not significant. Further factors that are significantly associated with the probability of correct recall are the STS scale and the number of items purchased.

The negative coefficient associated with the STS indicates that as the STS score is lower, the person is more of a tightwad, indicating that they spend less easily and that payments are more salient to them, and as a result would be remembered better. Our results show support for this intuition. As the number of items increases, the probability of correct recall decreases, as in Study 1. Last, as the time between the shop and the survey increases, participants find it more difficult to recall their spending exactly, which is line with the literature on memory.

In line with the analysis of Study 1, we also ran a logistic regression and continue to find that our results are qualitatively and quantitatively similar (see Appendix 3B). Additionally, we also ran a linear model exclusively looking at the participants who filled in their survey on the same day as they did their shopping ($n = 523$), as a robustness check (see Appendix 3E). We continue to find an effect of contactless. The magnitude of the effect is the same, reducing the probability of correct recall by approximately 6%, when compared to cash. Within the same-day sample this effect has lost significance due to the increase in the size of the confidence intervals, which is due to the reduction in sample size, making it impossible to exclude a positive effect. We see this result as a robustness check indicating that the effect of contactless payment methods on expenditure recall is around a 6% reduction in accuracy, compared to cash.

	<i>Dependent variable:</i>
	Probability Correct
Contactless Debit Card	−0.059** (−0.101, −0.016)
PIN-verified Card	−0.025 (−0.076−0.027)
Pain of Paying	−0.005 (−0.096−0.087)
Income	0.004 (−0.007−0.015)
Monthly Grocery Spend	0.007 (−0.0004, 0.015)
Being on a Budget	−0.005 (−0.045, 0.034)
Spendthrift Tightwad Scale	−0.007* (−0.014, −0.0002)
Number of Items	−0.006*** (−0.008, −0.004)
Point of Sale	0.009 (−0.029, 0.046)
Time Difference	−0.010 (−0.021, 0.001)
Question Order	−0.007 (−0.042, 0.029)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	1,089
R ²	0.062
Adjusted R ²	0.044
Residual Std. Error	0.299 (df = 1,067)
F Statistic	3.386*** (df = 21; 1,067)
Reference level payment method	Cash
Reference level being on a budget	No
Reference level point of sale	Cashier
Reference level question order	estimate, pain of paying
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001

Table 3.4: A linear probability model of the probability of correct recall in Study 2.

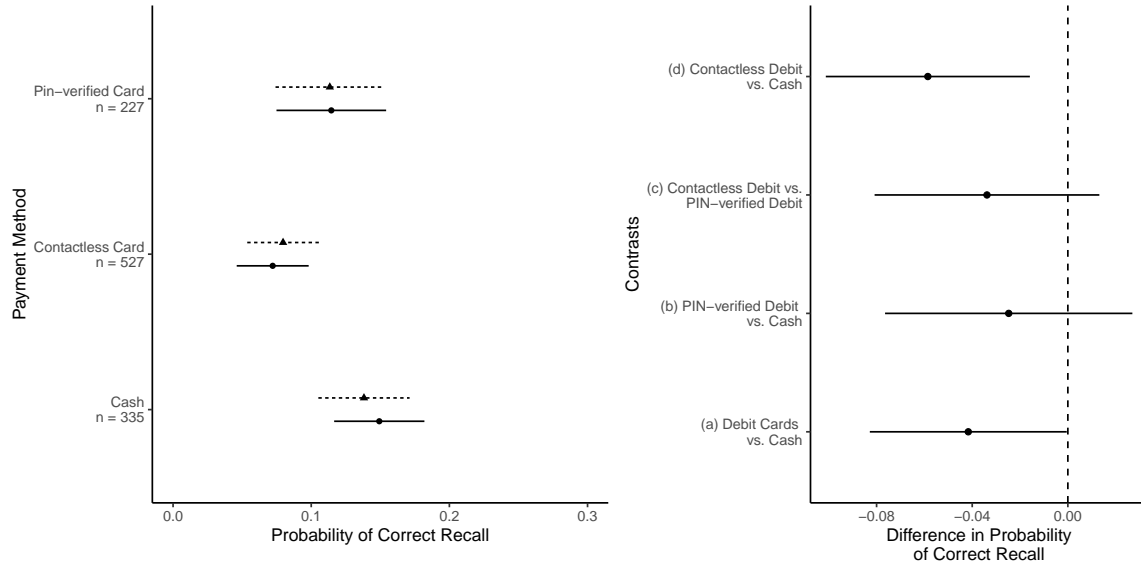


Figure 3.2: Results of Study 2. The solid lines with the circular markers in the left panel show the marginal effect of payment method and its confidence intervals, derived from the linear model of the probability of correct expenditure recall. Estimations were averaged over levels for factor variables, weighting levels by their frequency in the data. The dashed intervals with triangles show the effect of payment method without covariates. The right panel shows the pre-registered contrasts for Study 2. Error bars are 95% confidence intervals.

To estimate the effects of contactless payment methods, we consider the following contrasts (a) debit cards vs. cash, b) PIN-verified debit card vs. cash, (c) contactless debit card versus PIN-verified debit card and (d) cash versus contactless debit card.

When comparing the average of the two types of payment cards to cash, we find that the estimated probability of recalling expenditure correctly is 4.2% (95% CI [0.0%, 8.3%]) lower with cards than with cash (see contrast (a)). Comparing PIN-verified debit cards to cash, we find that the estimated probability of recalling expenditure correctly is 2.5% (95% CI [2.7%, 7.7%]) lower with PIN-verified cards (see contrast (b)). Comparing contactless debit cards to PIN-verified cards we find that the estimated probability of recalling expenditure correctly is 3.4% (95% CI [-1.3%, 8.1%]) lower with contactless (see contrast (c)). Last, comparing contactless debit cards to cash, we find that the estimated probability of recalling expenditure correctly is 5.9% (95% CI [1.6%, 10.1%]) lower with contactless (see contrast (d)).

In line with the analysis from Study 1, we also considered the effect of the number of items purchased, which in Study 2 was coded as a continuous variable. An alternative coding for number of items, single vs. multi-item, reveals that expenditures from single-item transactions are 29.8% (95% CI [20.7%, 38.9%]) more likely to be recalled correctly (see Appendix 3D).

In addition to establishing the role of payment method on the accuracy of expenditure recall, we were also interested in the effect of the payment method on the pain of paying, and the indirect role (mediation) the pain of paying may play in influencing the accuracy of recall. Table 3.5 shows the coefficients from a linear model regressing the pain of paying on payment method, and a variety of covariates. Estimates from this model are shown in Figure 3.3. The left panel of the figure shows the estimated marginal mean effect of payment method on the pain of paying, both in the model with only payment method as regressor (dotted line) and the model with all the covariates (solid line).

Table 3.5 shows there is no significant difference in pain of paying between contactless debit cards, PIN-verified debit cards and cash, contradicting prior literature.

Factors associated with significant increases in the pain of paying are the monthly grocery spend, the STS, the number of items purchased and being on a budget. It is in line with previous literature that those who are on a budget are more likely to pay more attention to how much they are spending; paying is more salient to them, and so more painful. The same holds for the STS, where the pain of paying is higher for those more towards the tightwad end of the scale. The coefficient for number of items shows that paying is perceived as more painful the more items are purchased, which is intuitive given the correlation between number of items purchased and money spent. The results also suggest that those who spend more on groceries monthly find it more painful to pay.

Factors associated with significant decreases in the pain of paying are the point of sale - using the self-service check out, the time difference and the question order. As self-service check outs tend to be quicker, this suggests that quicker transactions tend to be less painful. The time difference shows that the more time has passed since the grocery shop itself, the less pain is experienced when the consumer recalls the expenditure. This might be due to the memory of the expenditure no longer being very salient. The question order shows that when participants are first asked to rate their pain of paying and then estimate the expenditure, they experience less pain of paying than if the order is reversed, suggesting that recalling how much was spent may evoke higher levels of pain of paying.

	<i>Dependent variable:</i>
	Pain of Paying
Contactless Debit Card	−0.024 (−0.052, 0.004)
PIN-verified Debit Card	−0.014 (−0.048, 0.020)
Income	−0.003 (−0.010, 0.004)
Monthly Grocery Spend	0.005* (0.0004, 0.010)
Being on a Budget	0.049*** (0.024, 0.075)
Spendthrift Tightwad Scale	0.008*** (0.004, 0.013)
Number of Items	0.001* (0.0001, 0.003)
Point of Sale	−0.043*** (−0.068, −0.018)
Time Difference	−0.009** (−0.017, −0.002)
Question Order	−0.026* (−0.049, −0.002)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	1,089
R ²	0.089
Adjusted R ²	0.072
Residual Std. Error	0.196 (df = 1068)
F Statistic	5.209*** (df = 20; 1068)
Reference level payment method	Cash
Reference level being on a budget	No
Reference level point of sale	Cashier
Reference level question order	estimate, pain of paying

Note: *p<0.05; **p<0.01; ***p<0.001

Table 3.5: A linear model of the pain of paying in Study 2.

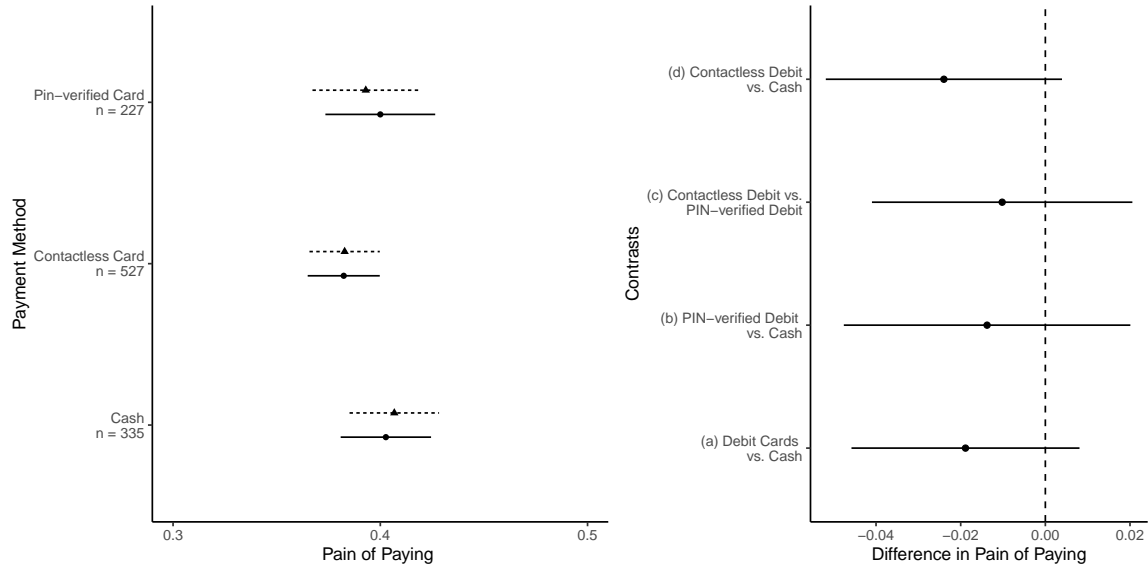


Figure 3.3: Results of Study 2. The solid lines with the circular markers in the left panel show the marginal effect of payment method and its confidence intervals, derived from the linear model of the pain of paying. Estimations were averaged over levels for factor variables, weighting levels by their frequency in the data. The dashed intervals with triangles show the effect of payment method without covariates. The right panel shows the pre-registered contrasts from Study 2. Error bars are 95% confidence intervals.

Figure 3.3 shows consistent effects of payment method across models with and without covariates. Looking at the contrasts shown on the right panel, we see that the self-reported pain of paying is .02 (95% CI [-.01, .05]) higher with cash than with the two types of cards (see contrast (a)) and .01 (95% CI [-.02, .05]) higher with PIN-verified debit cards than with cash (see contrast (b)). Comparing contactless debit cards to PIN-verified cards, we find that the pain of paying is .01 (95% CI [-.02, .04]) lower with contactless (see contrast (c)). Last, the pain of paying is .02 (95% CI [-.00, .05]) lower with contactless than with cash (see contrast (d)). However, all of the four contrasts include zero in their confidence interval, indicating that the differences are not significant. Our Sobel mediation test supports these findings, showing that the mediation looking exclusively at accuracy of recall, payment method and pain of paying is non-significant ($p = .75$). We only include these variables in the mediation test to avoid any interaction between other variables.

3.4 Discussion

We explored how payment methods affect the accuracy with which expenditures can be recalled. In two studies, we found that recall accuracy was lower for contactless payments than cash payments. Study 1 measured recall immediately after a shopping trip, showing an association between contactless payment and poorer expenditure recall. In Study 2,

because participants were randomly assigned a payment method for their usual shopping trip, we were able to find a causal link between contactless payment and poorer recall. Results for PIN-verified payments were less consistent. In Study 2, accuracy levels for PIN-verified payments fell between contactless (worst recall) and cash (best recall). In Study 1, accuracy levels for PIN-verified payments were worse than for contactless (medium recall) and cash (best recall), but these differences were only significant for credit cards, not debit cards.

It may be relevant that PIN-verified transactions have features that may impact expenditure recall. While they tend to be shorter than cash transactions and longer than contactless transaction, they also involve retrieving the PIN from memory, which may interfere with memorising and recalling the total expenditure. From a memory perspective, the duration of the transaction suggests that recall should be better than with contactless, but worse than cash (e.g., Magnussen et al., 1991). On the other hand, recalling the PIN may reduce the accuracy with which expenditure is recalled. This second effect may be less prominent when recall immediately follows the expenditure, as in Study 1, than when recall happens hours or days later, as in Study 2.

The differences between contactless and cash found in Study 1 are compatible with the pain of paying hypothesis. In Study 2, we tested for direct and mediated effects of the pain of paying, but found that the self-reported pain of paying did not differ between payment methods. Our findings are in line with those of Banker et al. (2017), who found that shopping with credit cards did not lead to lower pain of paying but lead to greater reward sensitivity. Pain of paying did decrease with the time between the survey and the shop, and was higher when elicited after recalling the expenditure, suggesting that it is likely to fade with time. If the behavioural effects of payment methods are driven by increased reward sensitivity and reduced price sensitivity, future research may need to focus on a more radical rethinking of the psychology of payments.

In both studies, the main driver of recall accuracy was the number of items purchased. Further analyses revealed that recall was most accurate with the purchase of a single item. Because with a one-item purchase people are exposed to the total expenditure twice (first on the shelf and then at the till) instead of just at the till, this finding lends further support to the memory account. The effect of contactless is small in comparison to this number-of-items effect, which in the comparison between single- and multi-item purchases is associated with a decrease in recall accuracy of just over 30% in Study 1, and almost 30% in Study 2.

In line with previous research (e.g., Rick et al., 2008), we found that the pain of paying was related to differences in self-rated spending tendencies. An interesting question for future research is whether people with different individual characteristics opt for different

methods. For instance, spendthrifts may have a natural inclination to use methods, like contactless cards, that facilitate spending, whereas tightwads may naturally use cash to curb their spending, as they do not enjoy spending money. The reverse may also hold true. Sophisticated consumers may pick the payment that counteracts their natural tendencies: tightwads would opt for cards if they want to spend without feeling too bad about it and spendthrifts could opt for using cash to curb their spending.

In both our studies, we found that contactless payment is associated with reduced expenditure recall accuracy. If this reduced recall translated into increased spending it is plausible that, in the longer term, the effects on personal finance may be substantial. Future research should look into the extent to which contactless increases the number of transactions people make and whether this results in detrimental effects on financial management. It would also be worth considering whether the use of online banking apps or expenditure trackers that aggregate over multiple accounts may mitigate any effects of new payment methods.

3.5 Conclusion

In two studies with a combined sample size of over 4,000 participants, we found that contactless payments lead to poor expenditure recall. This result was not mediated by the pain of paying. We speculate it may be related to the reduced salience of, and attention to, spending information during contactless transactions. Whilst the exact mechanism behind the effect remains unknown, its implications are important, as poor expenditure recall can plausibly lead to larger issues in personal finances.

Appendix 3.A A General Linear Probability Model of Correct Recall for Study 1.

	<i>Dependent variable:</i>
	Probability Correct
PIN-verified Credit Card	−0.828*** (−1.318, −0.338)
PIN-verified Debit Card	−0.317 (−0.640, 0.005)
Contactless Credit Card	−0.423 (−0.856, 0.010)
Contactless Debit Card	−0.311* (−0.620, −0.002)
Contactless Mobile	−0.260 (−0.645, 0.125)
Number of Items (2)	−1.352*** (−1.567, −1.138)
Number of Items (3)	−1.588*** (−1.832, −1.344)
Number of Items (4)	−1.676*** (−1.997, −1.356)
Number of Items (>=5)	−2.263*** (−2.547, −1.978)
Point of Sale	−0.117 (−0.356, 0.122)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	2,922
Log Likelihood	−1,694.873
Akaike Inf. Crit.	3,431.746
Reference level payment method	Cash
Reference level number of items	1
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001

Table 3.6: A general linear probability model of the probability of correct recall in Study 1.

Appendix 3.B A General Linear Probability Model of Correct Recall for Study 2.

	<i>Dependent variable:</i>
	Probability Correct
Contactless Debit Card	−0.628* (−1.108, −0.148)
PIN-verified Debit Card	−0.211 (−0.759, 0.336)
Pain of Paying	0.112 (−0.921, 1.144)
Income	0.065 (−0.057, 0.187)
Monthly Spending on Groceries	0.064 (−0.014, 0.143)
Being on a Budget	−0.048 (−0.492, 0.395)
STS scale	−0.081* (−0.161, −0.001)
Number of Items	−0.108*** (−0.144, −0.071)
Point of Sale	0.078 (−0.348, 0.503)
Time Difference	−0.168 (−0.342, 0.006)
Question Order	−0.044 (−0.453, 0.364)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	1,089
Log Likelihood	−323.763
Akaike Inf. Crit.	691.525
Reference level payment method	Cash
Reference level being on a budget	No
Reference level point of sale	Cashier
Reference level question order	estimate, pain of paying

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 3.7: A general linear probability model of the probability of correct recall in Study 2.

Appendix 3.C A Linear Probability Model of Correct Recall, With a 1-Item Effect for Study 1.

	<i>Dependent variable:</i>
	Probability Correct
PIN-verified Credit Card	−0.208*** (−0.308, −0.108)
PIN-verified Debit Card	−0.086** (−0.151, −0.021)
Contactless Credit Card	−0.109* (−0.196, −0.021)
Contactless Debit Card	−0.079* (−0.141, −0.016)
Contactless Mobile	−0.073 (−0.151, 0.005)
Number of Items	−0.323*** (−0.357, −0.289)
Point of Sale	−0.048 (−0.097, 0.001)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	2,922
R ²	0.123
Adjusted R ²	0.118
Residual Std. Error	0.451 (df = 2904)
F Statistic	24.042*** (df = 17; 2904)
Reference level payment method	Cash

Note: *p<0.05; **p<0.01; ***p<0.001

Table 3.8: A linear probability model of the probability of correct recall in Study 1, where the number of items is measured as a binary variable with 0 indicating only a single item was purchased, and 1 indicating multiple items were purchased.

Appendix 3.D The 1-Item Effect for Study 2.

	<i>Dependent variable:</i>
	Probability Correct
Contactless Debit Card	−0.062** (−0.105, −0.020)
PIN-verified Debit Card	−0.031 (−0.082, 0.021)
Pain of Paying	−0.018 (−0.109, 0.073)
Income	0.003 (−0.008, 0.014)
Monthly Grocery Spend	0.009* (0.001, 0.016)
Being on a Budget	−0.003 (−0.043, 0.036)
Spendthrift Tightwad Scale	−0.006 (−0.013, 0.001)
Number of Items	−0.298*** (−0.389, −0.207)
Point of Sale	−0.017 (−0.053, 0.020)
Time Difference	−0.010 (−0.021, 0.001)
Question Order	−0.007 (−0.043, 0.028)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	1,089
R ²	0.068
Adjusted R ²	0.050
Residual Std. Error	0.299 (df = 1067)
F Statistic	3.699*** (df = 21; 1067)
Reference level payment method	Cash
Reference level being on a budget	No
Reference level point of sale	Cashier
Reference level question order	estimate, pain of paying

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 3.9: A linear probability model of the probability of correct recall in Study 2, where the number of items is measured as a binary variable with 0 indicating only a single item was purchased, and 1 indicating multiple items were purchased.

Appendix 3.E The Same Day Effect for Study 2.

	<i>Dependent variable:</i>
	Probability Correct
Contactless Card	−0.061 (−0.127, 0.005)
Pin-verified Card	0.017 (−0.064, 0.099)
Pain of Paying	0.033 (−0.109, 0.175)
Income	0.008 (−0.009, 0.026)
Monthly Spending on Groceries	0.014* (0.002, 0.026)
Being on a Budget	−0.007 (−0.071, 0.056)
STS scale	−0.012* (−0.023, −0.001)
Number of Items	−0.007*** (−0.010, −0.004)
Point of Sale	−0.009 (−0.070, 0.051)
Question Order	−0.018 (−0.076, 0.040)
Time of Day Dummies	Yes
Day of the Week Dummies	Yes
Constant	Yes
Observations	523
R ²	0.093
Adjusted R ²	0.057
Residual Std. Error	0.331 (df = 502)
F Statistic	2.564*** (df = 20; 502)
Reference level payment method	Cash
Reference level being on a budget	No
Reference level point of sale	Cashier
Reference level question order	estimate, pain of paying

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 3.10: A linear probability model of the probability of correct recall in Study 2, exclusively looking at the people who filled in the survey on the same day (n = 523). The sample division is as follows: Cash (n = 190), Contactless (n = 230), PIN-verified (n = 103).

Chapter 4

First Contactless: The Effect of Contactless Payment Methods on Spending, Debt, Savings and Cash Usage

4.1 Introduction

Since the launch of credit cards in 1958 and the launch of debit cards in 1992, cash payments have been increasingly replaced with payments by value-holding cards. In 2004, most people in the UK spent more money using cards than cash (UK Cards Association, 2019). Despite being one of the first countries to launch contactless payments, uptake of contactless spending in the UK was slow. Contactless payments became popular only after 2016, and now account for over 60% of all transactions (Campbell, 2015). Continental Europe and Australia adopted contactless payments more enthusiastically, contactless payments accounting for 50% (Statista, 2020a) and 80% (WestPac, 2017) of all transactions, respectively .

Despite contactless' ubiquity, research on contactless payments remains scarce. Existing work points toward an increase in spending when using contactless payments. A 2011 study by MasterCard produced results showing an increased usage of Mastercard's PayPass (classified as contactless) both in terms of value spending and transaction frequency. The study was conducted measuring the year-over-year growth for accounts that conducted "tap" transactions within the same 3-month time frame, sampled from three issuers. The overall results were a 30% increase in expenditure and an almost 50% increase in transaction frequency using contactless cards (MasterCard US, 2011). More

than 70% of the transactions were under \$25 and MasterCard argues that the increases can be explained by cash replacement. Trying to replicate the increase in spending associated with contactless, Trütsch (2014) uses the 2010 Survey of Consumer Payment Choice to estimate the impact of using contactless cards on the spending ratio at the individual level. Using propensity score matching to control for selection, the estimation shows that using contactless has a significant effect for both credit and debit cards. In agreement with MasterCard US (2011), Trütsch (2014) found an increase in expenditures, however the increase was much smaller. For credit cards, the usage of contactless was associated with an increase in the spending ratio of 8.3% at the point of sale, while the effect for retail and services purchases was 4.8% and 3.5%, respectively. For debit cards, the usage of contactless was associated with an increase in the spending ratio of 10% at the point of sale. The effect on retail and services payments resulted in a 4.5% increase. Seemingly, the effect of contactless holds stronger for debit cards than it does for credit cards. Comparing payment with cash, credit and contactless cards, See-To and Ngai (2019) find that the payment method significantly affects spending and awareness of spending. Approaching customers of a Hong Kong mall and asking them to indicate which payment they used and how much they had spent, they show that less accurate expenditure was associated with significantly increased willingness to spend, regardless of payment method. These increases in spending and willingness to spend are in line with qualitative research by James (2017), who shows, through semi-structured interviews, that a sample of British students experienced increased spending, reduced awareness of spending and reduced feelings of being in control of their finances when using contactless payments.

We see indicators of contactless methods of payment being associated with increased spending, more frequent spending and a sense of decreased awareness and control over spending. These factors have been empirically linked to debt accumulation. It is of societal importance to know whether contactless, as an even easier and quicker method of payment compared to cash and other card-based methods of payment, can lead to higher debt accumulation through reduced awareness.

We use a data set of over 300 million transactions provided by a Financial Aggregator App to see whether the onset of contactless usage leads to changes in money spent, frequency of spending, overdraft occurrence, unsecured loan usage, cash usage and savings. We do so by running an event study, comparing one year, specifically twelve months, before the onset of contactless usage to the twelve months afterwards. We will be applying a two-way fixed effects regression, accounting for both time and individual differences.

We find that contactless usage significantly increased spending, in both volume and value. Second, we find there to be no significant relationship between debt and the onset of using contactless. Third, and most counter intuitively, we find that the onset of

contactless usage significantly increases cash usage and savings. Last, we find that the onset of contactless usage directs more activity to the enabled account, accounting for approximately 70% of the increases in spending and savings.

Our research contributes to the existing literature in the following ways: we extend the existing theories on payment methods to fit a relatively new payment method: contactless (card) payments. Second, we use third party collected data to do so, rather than a survey based approach which is the most widely used method in earlier empirical work. Third, we use a large sample based in the UK, rather than the US. The advantage of doing so is that contactless payments have become popularised in the UK payment landscape, now accounting for over half the transactions, whereas they have yet to do so in the US payment landscape. Fourth, we test for the effect of the onset of contactless usage on spending, overdraft, debt, cash usage, and savings conjointly, rather than separately, as seen in the before studies, providing a clearer overview of the potentially wide-reaching effect of contactless payment methods.

4.2 Background

Payment methods have been shown to significantly affect personal finance, in a number of aspects. Research finds, when comparing credit cards to cash, that credit cards are associated with increased spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Soman, 2003; Tokunaga, 1993), worsened spending recall (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; Srivastava and Raghubir, 2002), decreased product attachment (Shah et al., 2016), reduced impulse control leading to more frequent spending (Omar et al., 2014; See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and debt accumulation (Gross and Souleles, 2002). However, these effects have been mainly established when comparing credit cards to cash. We are aware of a single study looking into the effect of willingness to pay when comparing debits cards to cash (Runnemark, Hedman, and Xiao, 2015), finding increased willingness to pay for debit cards.

The main theory in explaining the difference between payment methods is that of the “pain of paying”, by Zellermayer (1996), in which different methods of payment influence the way consumers feel about the payment. When using cash, consumers experience negative feelings during the transactions. These negative feelings are invoked by the physical handing over of the cash, the representation of value that cash signals and the concurrency of payment with the receiving of the good or service paid for. The reason these three aspects matter to the pain of paying is due to their influence on the ease and friction of the payment. Paying with cash is a long process, with the frictions of having

enough cash, counting cash, handing it over, getting some back etc., whereas paying by card has much less friction; there is no need for counting, nor exchanging hands. The card just gets swiped or tapped (in case of contactless), maybe a PIN needs to be entered. It is easier and faster. As a result, card payments are less painful.

So what is needed for a “painful” payment is physicality, value representation (transparency) and concurrency (Zellermayer, 1996). Different payment methods score differently on these criteria and can thus be considered more or less painful which then in turn can affect spending. Runnemark, Hedman, and Xiao (2015) argue that it is the lack of physicality and transparency leading to higher willingness to pay when using a debit card. Credit cards meet none of the three conditions; the credit card is neither physical, nor transparent, nor concurrent with the purchase. As such, the theory of the pain of paying is able to explain why these three different methods of payment (cash, debit and credit card), lead to such different results in the personal finance domain.

The pain of paying is not the only theory proposed to explain increased spending. Another theory is that of Soman’s transparency (2003). He proposed that it was mainly the lack of value denomination on cards and other methods, as compared to cash, that increased spending. The proposed transparency went both ways: the cards were unable to indicate how much was spent (lost), nor did they represent how much was left.

Srivastava and Raghurir (2002) proposed the theory of decoupling, focusing on the temporal dimension of payment. They argued that the reason consumers spend more and were less aware of their spending when using a credit card, as compared cash, was due to the fact that with cash the payment was immediate, but with credit cards the consumer had to wait until the end of the month to see the full statement, and make the actual payment for his or her purchases. It is true that with the introduction of online and mobile banking the consumer can accurately keep track of their spending, however, the reduced awareness of spending seen with credit cards persists (Thomas, Desai, and Seenivasan, 2011).

These theories focus almost exclusively on spending, but have been used to explain effects of reduced spending awareness as well (Raghurir and Srivastava, 2008). Reduced spending awareness has been linked to increased debt accumulation (Gross and Souleles, 2002). Gross and Souleles propose that if people cannot recall their spending accurately, they will not be able to update the mental account they have of their actual balance. As such, there will be a change in the actual account balance, but not in the mental account with which the consumer keeps track of their spending on that specific account. This makes it possible for consumers to spend their money “twice”. The consumer did not remember having spent money already and as such spends it again. This leads to people incurring overdraft fees and getting into debt on their real accounts, before they thought

they would according to their mental accounts. When mental accounting of this type is made more difficult through reducing a payment's memorability or salience, for example by reducing the pain of paying, the likelihood of receiving fees or charges to the accounts increases.

There is more to contactless than contactless cards. Mobile phones also have the option of being used as a contactless device and have received increased attention in research. Using a sample of over 25,000 US households from the 2015 National Financial Capability Survey (NFCS) Meyll and Walter (2019) find that using contactless mobile payments is associated with a 4.9% increase in the likelihood of exhibiting costly credit card behaviour. Frequent contactless mobile payment users are another 5% more likely to exhibit costly credit card behaviour compared to infrequent users. Meyll and Walter (2019) explain this increase in costly behaviour with the transparency framework (Soman, 2003) and the pain of paying (Zellermayer, 1996). Research by Garrett et al. (2014) shows strong associations between mobile payment adoption and high cost debt (payday loans, auto-title loans, etc.), financial mismanagement and costly credit card behavior (taking cash advances and paying over the limit fees). The authors suggest that users of mobile payment technology were focused on convenience, and they might be prone to impulse spending.

From previous empirical work there is a clear effect of payment method on personal finance management. In this research we are going to study how the introduction of contactless payment methods changes how people manage their personal finances. We hypothesize that:

Hypothesis 1 *The onset of contactless payment usage leads to a higher amount and frequency of spending.*

Hypothesis 2 *The onset of contactless payment usage leads to a higher cost and occurrence of overdraft fees.*

Hypothesis 3 *The onset of contactless payment usage leads to a higher occurrence of unsecured debt.*

Hypothesis 4 *The onset of contactless payment usage leads to a decrease in cash usage, both in volume and frequency.*

Hypothesis 5 *The onset of contactless payment usage leads to a decrease in savings.*

Hypothesis 6 *The onset of contactless payment usage leads to an increase in credit debt.*

4.3 Method

4.3.1 Data

We analyse data from a Financial Aggregator App in the UK. The data spans 2012 to 2020 and represents the data of just under 300,000 users. Users sign up for the Financial Aggregator App and link all of the accounts they would like to track via the app. Even if users stop using a specific account, data collection by the app only ceases when users explicitly remove the account from the app.

Users are identified by a unique identifier. Information on users includes the year of birth, gender, (anonymised) postal code, salary range (within 10k increments) upon first using the app, overdraft balance upon first using the app and their account references within the app.

Each bank account tracked by the app is identified by a unique identifier. Information on accounts includes what type of account it is (savings, credit card, current, other), the account provider (bank), and the account balance.

Information at the transaction-level includes the amount debited or credited to the account, the date of the transaction, the type of transaction as classified by the user, the system, and both the user and system. It is the latter that we use for identifying the spending categories we created. It also shows who the recipient or sender of the transaction is, but a lot of information here has been removed if there were internal transfers or transfers to bank accounts belonging to other individuals. Most importantly, we have access to the transaction description which is a single string often detailing the type of payment and all of the information mentioned above, with the exclusion of the private banking details of an individual.

4.3.2 Sample

Through the transaction description, we were able to identify which providers did and did not flag contactless payment methods. Our sample is derived from those providers who do flag contactless, excluding all the others. This left us with 26 different providers, and reduced our original sample size by one third (Table 4.1).

We decided to only look at current accounts in our analysis. It is up to the users discretion how many accounts, and which type of account, they sign into the app to track. Most users did sign up at least one, or several current accounts, but numbers are much lower for the other types of accounts (credit card, savings, other). We believe that these users do own these types of accounts, as statistics bare out that the average British consumer does hold at least one current account, one savings account and one credit card (Statista, 2021b; Finder, 2021). Additionally, numbers indicate that 47% of the British banking population hold at least two current accounts (Statista, 2021b). These numbers provide an indication that most of the app users do own these accounts, but simply decided not to track them. As a result we did not have a complete picture of the changes that happen between these accounts as a result of contactless usage, and decided to only focus on the current accounts.

Further restrictions focused on the number of accounts held by an individual. The maximum number of current accounts held by an individual user was found to be 309. This number of current accounts does not signal that the user is only looking into their own personal finances. As a restrictive measure, we only looked at people with 5 current accounts or less. Just under 90% of users do not hold over 5 current accounts and remained in our sample.

Next, we restricted ourselves to only look at the users that started using contactless. Using the detailed transaction descriptions we were able to derive whether the transaction was paid for using a contactless payment method. Each transaction that included the string “contactless” or “clp” was flagged as “Contactless”. From thereon, it could be established when contactless was first used with a specific current account, and to which user it was linked. That date was then marked as its first usage. This date then became month 0 as a time reference point. Besides the account needing to have started using contactless, we also required the account to have at least one year of data before starting to use contactless, so twelve months before (-12) and to have at least one year of data after starting to use contactless, so twelve months after (+12). All of the analysis is relative to the starting point of using contactless. We were then left with 43,850 users and 90,551 accounts of which less than half was contactless activated.

As we wanted to have a complete picture of the user when starting to use contactless, we needed to ensure that a user holds more than one current account: one contactless activated and one not contactless activated. We filtered out all the users who only had one account registered and are left with a sample of 25,939 users with 72,640 accounts.

Our last time-based restriction was to limit our data to only the twelve months before and after the introduction of contactless, to the account. For each account we now hold only 25 months of data. This further reduced our observations, but not our users and

	Number of Transactions	Number of Account Months	Number of Users	Number of Accounts
Total	676,433,185		271,856	1,320,670
Providers Who Flag Contactless	464,598,947		225,814	938,627
Current Accounts No More Than 5	412,022,287		218,983	485,729
Current Accounts Exclusively Looking at	366,259,511		207,743	390,816
Contactless Users Users that Hold	9,2019,829		43,850	90,551
More than One Account	64,749,580		25,939	72,640
Restricting to Two Years of Data	32,088,856		25,939	63,730
Changing Unit to Per Month		725,638	25,939	63,730
Excluding 2020		706,174	23,283	60,800
Balanced 75% of Months		262,797	4,875	11,324
Users that Hold Both Account Types		53,467	2,245	5,113

Table 4.1: Table showing the different sample restrictions and their effect on the sample size, measured in transactions, account months, number of users and number of accounts included in the sample.

accounts. After this step we balanced our sample, ensuring that they had data for at least 75% of these 25 months, leaving us with 4,875 users and 11,324 accounts for our analysis. Due to the balancing, some accounts no longer appeared in the data, because not every user had an account in both data sets (the contactless account set and the non-contactless account set). Ensuring that users still held one contactless current account and at least one non-contactless current account we filtered out those that do not, and were left with a sample of 2,245 users with a total of 5,113 accounts, of which 2,245 are contactless and 2,868 are non-contactless. All of these reductions and there effect on the sample can be seen in Table 4.1.

4.3.3 Variables

Our main analysis entailed eleven dependent variables, measured on a per-month basis:

- Spending was measured by both volume and value. The volume was the *number of transactions*, simply measured as the number of transactions in the month on this

account. The *total monthly spend* was defined as all debits out of the account, that were not internal transfers between accounts, savings, investments or repayments.

- The *cost of overdraft fees* was created by flagging overdraft fees within the transaction description and the internal categorisation mechanism of the data. The debit amounts of money associated with this string were summed per month and indicate the cost of the overdraft fees per month. The *likelihood of incurring an overdraft fee* is measured as a binary dummy, 0 indicating the user did not incur an overdraft fee within that month, 1 indicating that they did.
- The *likelihood of incurring unsecured debt* was created by flagging several forms of unsecured debt, such as unsecured loans and payday loans, within the transaction description of the data and the internal categorisation mechanism. The credit amounts of money associated with this string, such as receiving of the money associated with the loan, were summed per month. The likelihood of holding this type of debt is measured as a binary dummy, 0 indicating the user did not hold unsecured debt within that month, 1 indicating that they did.
- Cash usage was flagged by finding cash withdrawals within the transaction description and the internal categorisation mechanism of the data. Summing those frequencies, we arrive at the *number of cash withdrawals*. Using the debits associated with the cash withdrawals, we find how much cash was withdrawn that month, arriving at the *value of cash withdrawals*.
- *Savings* were flagged by both looking into the transfers from the current account into accounts that were registered as savings accounts, as well as looking into the transfers into the current account from accounts that were registered as savings accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of savings, and calculate the difference between these. Positive coefficients means that more money was moved into the savings account(s) than money was taken out out of the savings account(s).
- *Credit card debt* was flagged by both looking into the transfers from the current account into accounts that were registered as credit accounts, as well as looking into the transfers into the current account from credit card accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of the credit account, and calculate the difference between these. Positive coefficients means that more money was moved into the

credit account(s) than money was taken out of the credit account(s). Negative coefficients mean that the credit card debt is increasing.

- To account for account activity we also created two variables measuring the money coming into the account. *Credits* were flagged by looking into all the money being transferred into the account, without exclusions. These transfers would include income. To check for inter-account activity we looked at *internal transfers*, which are a measure of all the money coming into the account for which we have no information - these are other accounts of the user for which information is removed for privacy reasons. Income was excluded from this measure.

In addition to the main variables of interest outlined above, we also looked into the spending categories. Sixteen spending categories have been derived and classified from the data, using the internal categorisation mechanism, which follows the apps's category guidelines and can be adjusted by the individual user as they see fit.

Last, all of the variables which are based on spending (e.g. are measured in pounds) have been winsorized and exclude the bottom and top 5% to reduce outliers.

With regards to the independent variables, we account for income of per month, measured in the total money going into the measured account (credits), excluding internal transfers. As seen with spending, we looked at the distribution of income and exclude the bottom and top 5% to reduce outliers. In total there were only two independent variables: contactless usage and income.

All eleven outcome variables were measures of personal finance management and we ran eleven separate fixed effects regressions using individual and time fixed effects. We included separate fixed effects for the user (as identified by the user identifier) and for time at the monthly level. In addition to accounting for both time and individual effects, the dependent variable, contactless usage, is a dummy variable which is either 0 (before contactless usage) or 1 (after contactless usage). This dummy is different for each account and each user, as it was computed with respect to each individual's month 0. Table 4.2 shows the summary statistics of the variables of interest, before and after the onset of contactless usage.

4.3.4 Analysis

To establish the effect of the onset of contactless payments on personal finance, we ran a set of eleven fixed effect regressions on our eleven dependent variables. Within our regressions we tested for the effect of income and contactless usage, accounting for the fixed effects for both the individual and calendar time.

	Before Contactless			After Contactless		
	Mean	SD	Median	Mean	SD	Median
Number of Transactions	79.1	52.5	70	86.8	55.1	77
Spending (in £)	2,005	1,713	1,529	2,170	1,768	1,694
Cost of Overdraft (in £)	4.62	16.6	0	4.7	17.2	0
Number of Cash Transactions	2.96	4.35	1	2.85	4.1	1
Cash Spending (in £)	149	306	0	160	314	0
Savings (in £)	27.3	1,125	13.2	4.42	1,145	12.4
Credit Card Debt (in £)	-62.9	872	-3.18	-52.4	907	0
Credits into Account (in £)	3,404	3,169	2,478	3,676	3,297	2,709
Internal Transfers (in £)	639	1,375	30	684	1,408	50
Income (in £)	4,340	3,680	3,250	4,650	3,730	3,530

Table 4.2: Table showing the summary statistics of the variables of interest for the sample of all of the payment accounts from the sample of 2,245 contactless users.

With regards to calendar time, this was measured in the month of transaction. The month of transaction is a counting measure starting at “1”, which represents the very first month in the data, which is January 2012. The last month is the data is month “105”, which represents June 2020. We accounted for time effects as we expected there to be differences in the economic situation that are influencing how money is being spent. As Table 4.1 has indicated, we excluded the year 2020 from our sample, as this is not a representative financial year.

With regards to the individual effects, the individual unit of measurement was that of the users. We made the active choice of starting our analysis at the contactless account level (Table 4.3, 4.4), having fixed effects for time and the individual user. We wanted to see whether the uptake of contactless payment methods on one account had effects on that account exclusively. To check for spillover effects into the personal finance management of the user in general, affecting the non-contactless active accounts, we ran the same analysis on the non-contactless accounts (Table 4.5), having fixed effects for time and the individual user. Last, we merged all those accounts to gain an overview of all accounts of the contactless user, to establish whether the onset of contactless payments impact the user as a whole (Table 4.6). We reiterate that the fixed effects were always focused on the individual user, and not that of the account. We believe that by looking at contactless active accounts, the non-contactless active accounts as well as looking at all the accounts

of the user combined, we are offering a complete and detailed picture of the effects of the onset of contactless payments on an account and individual user level.

4.4 Results

Looking at the total sample of 2,245 accounts using contactless, we find several trends within our eleven dependent variables. Figure 4.1 shows these trends. Across all eleven outcome variables, we see considerable movement both before and after the introduction of contactless payment on the contactless account. For number of transactions, total monthly spend, credits and internal transfers, we see that all tend to jump with the introduction of contactless. For overdraft fees, both cost and proportion we see movement, but no direct increase regardless the introduction of contactless. We see a similar trend with savings, although savings do display a slight upward trajectory. For cash withdrawals, we see a decrease in the number of cash withdrawals, but not in its value. We see a similar decrease for unsecured loans.

Looking at Table 4.3, we find evidence to support our first hypothesis: the number of transactions per month increases significantly by 4.49, and the total monthly spend increases significantly by £63.26. Interestingly enough, this is more than the increase in contactless spending, which accounts for only £33.54. We find contradictory evidence for hypothesis 2, as the cost and likelihood of incurring an overdraft fee marginally decreases by 24 pence and .2%. We do not find evidence to support our third hypothesis, as we find non-significant effects of contactless usage on unsecured debt occurrence. We find contrary evidence to our fourth hypothesis, predicting that contactless payment methods would replace cash. Cash usage however, has significantly increased in the number of transactions (.22), and the value of cash withdrawn increases by 36 pence. We find contrary evidence to our fifth hypothesis, as savings have significantly increased by £37.37 after the introduction of contactless payment. We do not find evidence to support our sixth hypothesis, as credit has decreased by 61 pence after the introduction of contactless payment, as shown in Table 4.3. This decrease does mean more credit debt has been taken out as compared to the debt being repaid. This number, however, is small and insignificant.

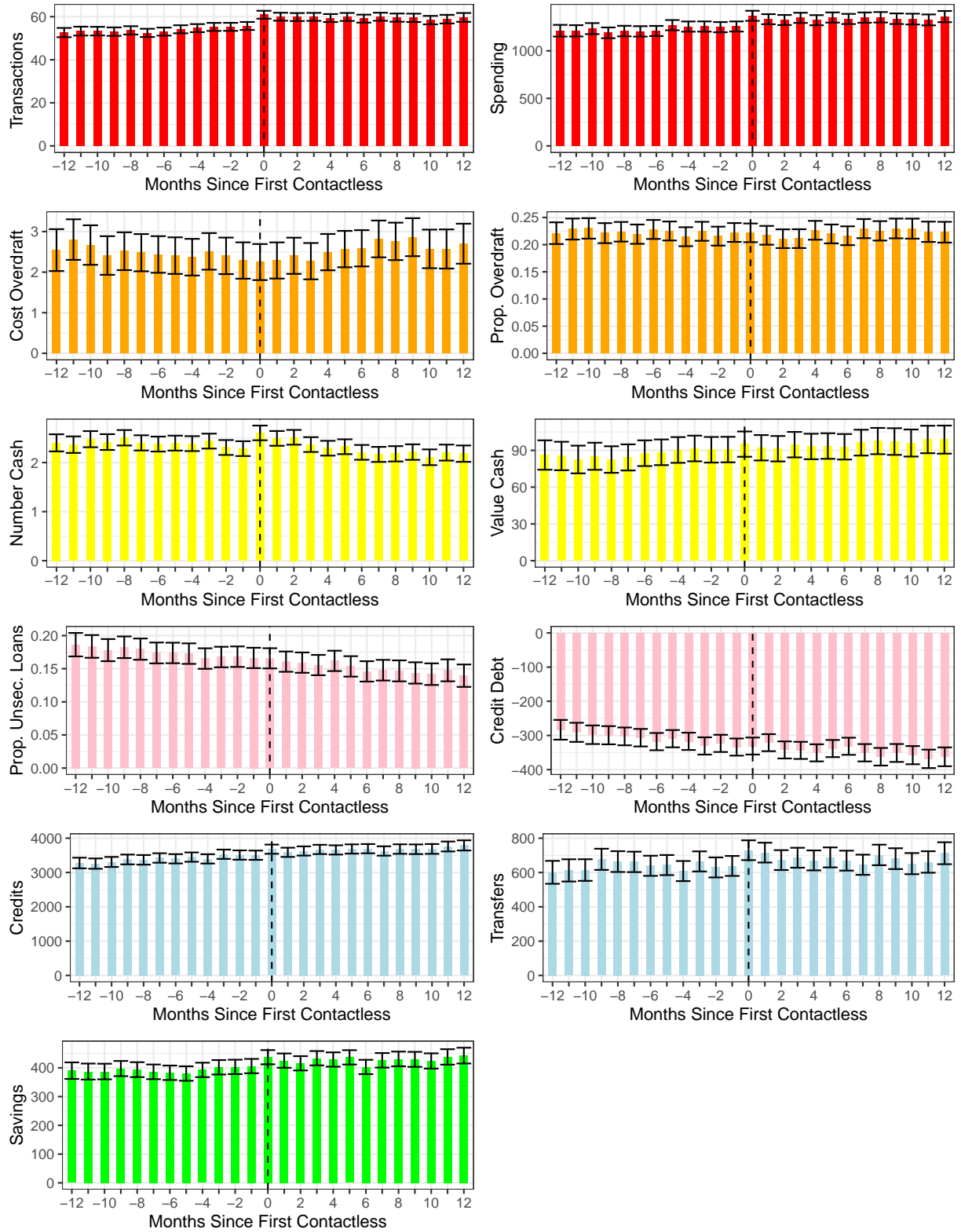


Figure 4.1: The effect of contactless usage on the eleven dependent variables, twelve months before and twelve months after uptake. The stippled line refers to point zero, which is the month in which contactless was first used. Confidence intervals are at 95%.

An increase of monthly spending of £63.26 is not a small increase for the average household. In addition to the significant increase in spending, we also have a significant increase in savings, totalling £100.63. We have controlled for income, and the resulting increase cannot be explained by an increase in monetary means. To explore this increase further we have looked at money moving into the account (Table 4.3). With the onset of contactless usage we see that significantly more money is being credited into the account, at a value of £57.95, explaining just over half of the additional debits (both savings and spending) on the contactless active account. We see that this additional influx of money can be entirely explained by manual transfers from the user’s other accounts (not registered with the app) onto the contactless active account which is registered onto the app. This indicates that with the onset of contactless usage, the contactless active account increases in its activity, possibly at the expense of activity on the other spending accounts of the user.

In addition to finding additional spending due to contactless usage, we are also interested in whether there is a category shift in terms of spending, with the onset of contactless. We aim to find this shift by looking into the sixteen different spending categories as identified by the internal categorisation system. The reason for doing so is that it is assumed that contactless payment methods favour smaller, more impulsive spends. So we do expect to see a shift in how money is being spent with regards to the different spending categories, as of the introduction of contactless payments to the account. Table 4.4 shows that contactless spending does have an effect on how money is divided across categories. We see that spending on housing, measured in mortgage and rent, increases minimally (£6.25), and so does spending on the home, which can range from DIY to gas and electricity to buying houseplants, by £15.34, which is significant. Contactless uptake is also associated with a significant increase in spending on groceries (£13.87), health (£0.58), going out (£7.34), aesthetics (£4.68), gifts (£0.21) and one off spending (£0.11). We find that the onset of contactless usage does not significantly change spending on insurance, repayments, transport, children, hobbies, business, gambling and untagged expenditures. Untagged spending is spending for which the system hides most, if not all, information. It is likely that this type of spending is largely based on internal transfers from this account to other accounts of the user, and transfers to other financial contacts (e.g. repaying your friend as they paid for your half of the meal as well) as we are unable to see where the money is going, which is due to privacy protection.

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Loans (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Contactless Usage	4.49*** (0.43)	63.26*** (13.89)	-0.24 (0.18)	-0.002 (0.01)	0.003 (0.004)	0.22*** (0.04)	0.36 (2.06)	37.37*** (7.32)	-0.61 (7.05)	57.95** (22.15)	57.95** (22.15)
Income (in £100)	0.29*** (0.01)	16.86*** (0.50)	0.004 (0.002)	0.0002** (0.0001)	0.0002* (0.0001)	0.01*** (0.0007)	0.32*** (0.05)	4.02*** (0.20)	-4.47*** (0.22)	106.16*** (0.71)	6.16*** (0.71)
R ²	0.82	0.70	0.60	0.65	0.64	0.71	0.84	0.68	0.66	0.88	0.37
Observations	51981	51981	51981	51981	51981	51981	51981	51981	51981	51981	51981
Accounts	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245
Users	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.3: The effect of contactless usage on the eleven dependent variables. Includes fixed effects for account and calendar year-month. Balanced sample of 2,245 contactless users and their contactless active accounts.

	Housing	Home	Groceries	Insurance	Repayments	Health
Contactless Usage	6.25* (3.16)	15.34*** (2.87)	13.87*** (1.91)	0.36 (0.65)	−0.37 (3.15)	0.58* (0.25)
Income (in £100)	0.69*** (0.08)	1.20*** (0.07)	0.59*** (0.04)	0.15*** (0.01)	0.95*** (0.08)	0.03*** (0.004)
R ²	0.77	0.76	0.77	0.66	0.66	0.48
Observations	51981	51981	51981	51981	51981	51981
Accounts	2245	2245	2245	2245	2245	2245
Users	2245	2245	2245	2245	2245	2245

	Transport	Children	Going Out	Hobby	Aesthetics	Gifts
Contactless Usage	10.54 (7.26)	0.09 (0.10)	7.34*** (2.03)	0.37 (0.44)	4.68*** (0.97)	0.21** (0.08)
Income (in £100) (0.001)	5.24***	0.01*** (0.23)	0.74*** (0.002)	0.07*** (0.04)	0.27*** (0.01)	0.005*** (0.02)
R ²	0.65	0.43	0.55	0.47	0.51	0.34
Observations	51981	51981	51981	51981	51981	51981
Accounts	2245	2245	2245	2245	2245	2245
Users	2245	2245	2245	2245	2245	2245

	Business	Gambling	One Off	Untagged
Contactless Usage	0.15 (0.15)	0.06 (0.11)	0.11* (0.05)	6.72 (10.95)
Income (in £100)	0.01*** (0.003)	0.01*** (0.002)	0.01*** (0.001)	10.29*** (0.33)
R ²	0.50	0.66	0.23	0.61
Observations	51981	51981	51981	51981
Accounts	2245	2245	2245	2245
Users	2245	2245	2245	2245

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.4: The effect of contactless usage on the sixteen different spending categories as identified by the system's own tagging. Includes fixed effects for user and calendar year-month. Balanced sample of 2,245 contactless accounts belonging to 2,245 users.

Despite the slight differences in identifying the monthly spending variable and the spending categories, we do see a significant increase in spending across seven spending categories with the onset of contactless usage. This is not explained by an increase in income, and has to be explained differently. We hypothesize that we are seeing a shift in how different payment accounts are being used. The onset of contactless usage makes the account on which it is activated easier to use, and as such preferred. Research on payment methods, contactless specifically, did find a clear preference for using this particular method as it was quicker, safer and easier (James, 2017). Our result with regards to increased account usage do seem to be supported by finding significantly more credits and internal transfers being moved into the contactless enabled account.

To test whether the increase in spending on the contactless activated accounts is caused by an increase of account usage, at the expense of non-contactless activated accounts, we look exclusively at the non-contactless accounts, and find a different relationship between our dependent variables and the onset of contactless payment usage (Table 4.5). We find no significant changes in any of the dependent variables and most coefficients remain positive, rather than turn negative. Negative coefficients would have indicated a compensation mechanism, explaining the significant increase in transfers into the contactless enabled account. Table 4.5, however, does not confirm our expectations of a compensation mechanism explaining the increases on the contactless enabled account by significant decreases in the non-contactless enabled account.

The changes in the dependent variables we have found for non-contactless accounts do not explain the changes we find with the contactless active accounts. To further investigate the effect of an account shift, as well as explain the additional spending and savings in excess of £100, we run an additional analysis on the user level, combining their contactless and non-contactless accounts. We look at the 2,245 users who have both contactless and non-contactless accounts, leaving us with a sample of 2,245 users, with 2,868 non-contactless accounts, and 2,245 contactless accounts, making for a total of 5,113 accounts. We run the same fixed effect analysis as we have done on the account level. The results of this analysis can be found in Table 4.6.

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Loans (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Contactless Usage	-0.43 (0.31)	1.51 (9.58)	0.07 (0.13)	0.00 (0.004)	0.003 (0.02)	-0.03 (1.30)	1.12 (1.16)	1.37 (3.63)	5.62 (5.22)	22.98 (15.14)	21.94 (15.71)
Income (in £100)	0.51*** (0.03)	16.89*** (0.70)	0.03** (0.01)	0.00*** (0.00)	0.0002* 0.0001	0.01*** (0.00)	0.83*** (0.17)	0.68*** (0.07)	-4.41*** (0.31)	103.44*** (0.77)	3.931*** (0.81)
R ²	0.75	0.65	0.58	0.58	0.61	0.57	0.72	0.54	0.60	0.89	0.34
Observations	58287	58287	58287	58287	58287	58287	58287	58287	58287	58287	58287
Accounts	2868	2868	2868	2868	2868	2868	2868	2868	2868	2868	2868
Users	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.5: The effect of the onset of contactless payment usage and income on the eleven dependent variables, for users that did use contactless payments, looking exclusively at their non-contactless enabled accounts. Includes fixed effects for the user and calendar year-month. Balanced sample of 2,868 accounts and 2,245 users.

Looking at Table 4.6, we find that most effects initially associated with contactless payments (Table 4.3) continue to persist, and some have become more extreme. We continue to see a significant increase in the number of transactions by 3.79, which is only slightly lower than the effect when exclusively looking at a contactless enabled account. The effect on spending, when looking on a user level has slightly increased and remains significant, at £70.63. The decrease in the cost of overdraft fees persist, yet the likelihood of obtaining overdraft fees has turned positive, yet both remain insignificant. On a user level, the onset of contactless payments has no significant effects on overdraft fees. The onset of contactless usage is also associated with an insignificant increase in the likelihood of incurring unsecured debt. There remains to be a significantly positive effect of cash usage, as measured in cash transactions made, although this effect is small (.18). The value in cash being withdrawn does not significantly change. Contrary to our fifth hypothesis and prior work, the significant increase in savings also continues to persist, having increased to £42.09. Also contrary to prior work, we find a small increase in credit as well, signalling that more money is going into the credit account (repayments) rather than being taken out on the credit card. This change, however, is small and insignificant.

To explore the increase in spending further, both in volume and value, as well as the continued increase in savings, we look into the credits and the internal money transfers made by the user for both these accounts. We find a large coefficient for credits (£82.01), however this is not significant. We do continue to find a significant increase in internal transfers of £78.73. This shift in internal transfers is not explained by a change in the non-contactless active accounts, but can be explained by a change in other spending accounts of the consumer. These accounts are not registered onto the Financial Aggregator App, and as such remain invisible to us. The increase in internal transfers *into* the accounts largely explains the increase in spending and savings associated with the onset of contactless usage. It is able to account for 69.8% of the increase.

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Loans (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Contactless Usage	3.79*** (0.58)	70.63*** (20.27)	-0.14 (0.26)	0.01 (0.01)	0.002 (0.004)	0.18*** (0.05)	3.90 (2.59)	42.09*** (7.91)	5.99 (8.68)	82.01 (43.18)	78.73* (33.10)
Income (in £100)	0.32*** (0.01)	15.40*** (0.42)	0.006* (0.003)	0.0002*** (0.0001)	0.0002*** (0.0001)	0.01*** (0.001)	0.40*** (0.05)	2.87*** (0.14)	-8.60*** (0.28)	1.26*** (0.01)	0.14*** (0.01)
R ²	0.81	0.69	0.68	0.67	0.62	0.72	0.84	0.67	0.65	0.80	0.44
Observations	53467	53467	53467	53467	53467	53467	53467	53467	53467	53467	53467
Accounts	4968	4968	4968	4968	4968	4968	4968	4968	4968	4968	4968
Users	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245	2245

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.6: The effect of contactless usage on the eleven dependent variables, for users that use contactless payments, looking at all their registered accounts, both those with and without contactless activated on them. Includes fixed effects for user and calendar year-month. Balanced sample of 5,113 accounts and 2,245 users.

4.5 Discussion

4.5.1 Findings

Our initial hypotheses predicted that the onset of contactless usage would increase spending, increase overdraft fees, increase unsecured debt, reduce cash usage, decrease savings and increase credit card debt. These hypotheses would be in line with previous empirical evidence and the theories on payment methods, such as the pain of paying. We find that contactless payment methods do not fit these findings and theories perfectly.

Spending

We find that contactless payment methods do significantly increase spending, in both volume and value, aligning with theories such as the pain of paying. The payment method is less physical, does not require a physical exchange of resources and is quick and easy. It only requires a tap for the payment to go through. As such, the payment method does fit within the pain of paying theory.

What is more interesting than contactless spending itself going up, is the possibility of it being brought about by a compensation mechanism, where the spending of the contactless account is filtered away from non-contactless accounts. Having looked further into the increase in spending, which could not be explained as a wealth effect as we also controlled for income, we do find that the onset of contactless payments on one account, does direct some attention and usage towards this account. However, when looking at non-contactless accounts, we do not find a significant decrease in any of the variables of interest, rather, some of them slightly increase. Merging the account types, we continue to find a significant increase in the number of transactions, spending, cash usage and savings. We find that the uptake of contactless is associated with a significant increase of spending volume and frequency, by 3.79 transactions and £70.63.

To further account for this significant increase in spending and savings we looked into the internal transfers into the contactless account and did find a significant increase which can largely explain the increase in spending on both the contactless account level and the user level. As such, we do find a compensation mechanism, but the mechanism applies to accounts that have not been registered onto the app, and as such remain invisible to us.

Debt

The link between contactless payments and debt, measured in overdraft fees and unsecured debt, remains insignificant throughout, indicating that the onset of contactless usage does not change people's control of their immediate spending, and their accurate updating of

their remaining balance, otherwise they would be receiving overdraft fees. This is contrary to previous research, especially that by James (2017) who found that UK students felt less in control of their finances when using contactless and felt as if they were less aware of their spending.

Moving from accounts that are associated with contactless payments to those who are not, we see no significant change associated with the onset of contactless usage either. Looking at both the accounts on the user level, we find that contactless payments do not have a significant impact on the cost of overdraft fees, nor the likelihood of obtaining them.

Looking at the second form of debt, unsecured loans (e.g. payday loans), we do not find a significant increase in the likelihood of having this type of debt, when exclusively looking at contactless accounts. This does seem to indicate that the increased spending we find with contactless usage does not take a toll on personal finance to the extent where taking on debt, in the form of a loan, is found to be a desirable option. This finding persists for non-contactless accounts. When looking on a user level the likelihood of incurring unsecured debt remains insignificant.

Our results with regards to overdraft fees and unsecured debt move in the opposite direction of the previous research, especially the pain of paying, as we do not find a significant increase of debt. This finding is contrary to earlier research on mobile payment methods, which can be classified as a form of contactless payment methods (Meyll and Walter, 2019; Garrett et al., 2014). It also contrasts with research by James (2017) who showed that contactless users felt like they were less in control of their finances. If their perception of losing control was based on feeling less in charge of their finances and spending to the level where they would eventually hold more, or higher cost debt. Our results do not support this perception.

Cash Usage

The relationship between contactless usage and cash usage is contrary to predicted. Contactless uptake leads to an increase in cash usage, but only in volume, when looking at the account level of contactless accounts. Its relationship was found to be significant throughout, but not of the direction that was originally expected. Although significant, the increase in the frequency of cash withdrawals is .22, yet the value of cash withdrawals does not significantly increase, seemingly indicating that people withdraw less cash each time they approach an ATM, however, do then find themselves in need of cash and get more out. The overall value withdrawn remains the same, but has been acquired over slightly more withdrawals. These numbers might be small, but given that cash has often

been heralded as a “budgeting tool” and might continue to be used as such, whether people felt that contactless transactions were not providing them with the same restraints, or not (Doyle et al., 2017).

This effect can be partially explained by the compensation mechanism we expected to see between contactless and non-contactless accounts. For non-contactless accounts we find that cash usage decreases in the frequency of withdrawals, but the value increases, although not significantly so. Looking on the overall user level, we do see that these opposite trends partially negate each other, as expected. On the user level, the number of cash withdrawals increases by .17 which is significant. The value of cash withdrawals also increases, but this increase is non-significant. Our fourth hypothesis of expecting reduced cash usage with the onset of contactless usage has to be rejected.

Savings

Looking at savings, we find the surprising result of significantly increased savings and we reject our fifth hypothesis. Savings, or at least the difference between money transferred from the current account to a savings account and the money transferred from the savings account to the current account has significantly increased by £37.37. We have trouble interpreting this result, as there is limited prior empirical evidence on the effect of concurrent payment methods on savings. As such it is difficult for us to say why this increase might have come to be.

Turning our eye towards the non-contactless accounts, we do not find a significant decrease in savings which would explain the increase in savings we see for contactless accounts. When looking on a user level, we continue to find a significant increase in savings of £42.09.

Similar to our findings with increased spending, we argue that the increase in savings is driven by the contactless account becoming the dominant account in use, as shown through increased internal transfer *into* the contactless active accounts. We expect there to be a compensation mechanism that may be driven by other accounts of the user that they have not registered on the Financial Aggregator App, meaning that those accounts remain invisible to us.

Credit

Looking at credit card debt, we find no significant change in credit debt usage and we reject our sixth hypothesis. Credit, or at least the difference between money transferred from the current account to a credit account (repayment) and the money transferred from the credit account to the current account (debt usage) has decreased by £.61, looking at

the contactless enabled accounts. Turning our eye towards the non-contactless accounts, we do not find a significant change in credit usage either. When looking on a user level, we continue to find a non-significant change in credit, but this has now turned positive. Similarly to our findings on debt occurrence as a result of new payment method usage, this result is contrary to prior research.

Account Activity

Last, looking at account activity, measured in both all the money credited into the account, as well as the money manually transferred into the account from the user's other spending accounts, we find a significant increase in account activity on the contactless active account (£57.95), as well as find an increase in internal transfers done by the user overall (£78.73). This shift is not explained by transferring money from the non-contactless account to the contactless account, however, is likely to be explained by transferring money from other accounts that are not registered on the app to the contactless enabled account. Whether these off-app accounts are current, savings or credit accounts remains unknown to us. In the case of those accounts being current accounts, what we are seeing is a shift in account usage, with the accounts that have easier payment methods enabled on them becoming the preferred account to use. Overall, this change in account activity is able to largely explain the significant increases in both spending and savings. On the contactless account level, the increase in internal transfers is able to explain 58.6% of additional debits, whereas on the user level the increase in internal transfers is able to explain 69.8% of additional debits.

4.5.2 Limitations

Despite our robust findings there are limitations to this research. A point of contention is the nature of the sample we are using. There is reason to believe that those who install and use a Financial Aggregator App on their phone are potentially a non-representative sample in the population. It can be argued that they are either very financially interested and knowledgeable, using the app to their advantage, whereas it is equally possible that this is a sample that is financially impaired and is trying to make sense of their finances by using this app. A combination of these two assumptions is also possible, potentially cancelling each other out when looking at all of the data in aggregate. Moreover, we found the average user within our sample to hold quite a larger number of accounts. As described above, we only analysed those with five current accounts or less, excluding 10% of our initial sample. This also leads us to believe that part of the original user base is non-representative, in that they hold more accounts than the average person would, if

they were only tracking their own finances, rather than those of others, or with regards to business enterprises.

An additional small limitation in our analysis, as made clear by the analysis of the spending categories, is that there is a number of untagged transactions within the data. We have no information on these transactions, as such it is difficult to see what their increased spending means for the personal financial situation of the user. However, this spending category is only associated with a non-significant increase of £6.74, explaining approximately 11% of the increase in spending. As such, we are confident in saying that not knowing the details of these transactions does not bias or reduce the robustness of our results.

4.5.3 Contribution

This research contributes to earlier empirical work in several ways. First, it shows that contactless payment methods do fit the already existing theories on paying, but not seamlessly. With regards to spending they adhere to the predictions made by these theories, which was their primary purpose. When looking into the effects on debt, cash and savings, the fit is no longer as seamless, showing no changes in debt and increases in cash usage and savings, contrary to the predictions made by prior theoretical work.

Second, we show that the onset of a new payment method on one account changes how that account is used. Our results show that the use of contactless payments on one account directs more attention and financial dealings to this account, at the expense of accounts that do not make use of this newer payment method. Whether this attention is derived from other current accounts, or from credit or savings accounts remains unknown.

Third, this research is unique in its methodology. Most of the prior work reviewed did not make use of third party data, most of the previous studies are grounded in lab work or survey responses. Our results bear higher levels of external validity as a result of this.

Fourth, we use a large sample based in the UK, rather than the US. As mentioned before, the advantage is that contactless payments have become normalised and popularised in the UK payment landscape, whereas this has not yet occurred in the US.

Fifth, we provide an overview of the effect of one new payment method, contactless, on a multitude of variables, rather than exclusively focusing on one aspect such as spending. Additionally, we provide analyses on both the user and the account level. We paint a more comprehensive and exhaustive effect of a potentially wide-reaching payment method.

Sixth, finding that the effect of contactless on debt occurrence, measured in overdraft fees, payday loans and other unsecured loans, is not as big as postulated by payment theories, or rather, is not present at all in these data, is a relief, given the level of societal

acceptance of this payment method. It is also a relief that cash still has a fighting chance, given that a reductions in either volume and value were not of the magnitude expected, nor of the direction expected. Cash remains to be a commonly used method of payment, which is good, given its budget-friendly constraints.

Last, our findings hint at the existence of other spending accounts that are not captured within this data. On a methodological level we show the difficulty of doing research when not having access to all of the user’s accounts and financial data. We do not discourage researchers from using data sets such as the one used here, but we do strongly recommend working with more complete data sets, such as those from financial institutions (e.g. banks), preferably the user’s main financial institution, to capture the whole picture of a user’s financial situation.

4.5.4 Further research

In addition to our findings here, further research is warranted to study the effect of payment methods on how we manage our personal finances. Most research focuses on only one aspect (e.g. spending, debt accumulation). We have attempted to paint a more complete picture, and we encourage future research to dive deeper as well.

We have to go beyond the payment methods as they currently stand. Contactless payment methods are not the most recent payment method to be introduced, yet research on these methods is already scarce. A newer payment method is that of mobile payments. Prior research has already looked into mobile payment methods, which can also be classed as contactless, although due to its multitude of features this classification might not be that accurate. It is important we also understand the effect of these payment methods on personal finance management, as it is especially the younger generations who start spending and managing their money using these methods.

As newer payment methods become increasingly faster available, and the pandemic and lock-downs have shifted the majority of spending online, we need to gain a better understanding of how these shifts, in both methods and settings, change the perception of money. We find that the increase in spending we find cannot fully be explained by contactless spending alone. The increase in spending is also driven by non-contactless spending, which increased as a result. It is important we understand the mechanisms at play here. Is it possible that the introduction of a “quick and easy” payment method changes how we feel about spending money? Or about how we relate to money in general? The pain of paying does indicate that as payments become easier and quicker, that they are less painful and less salient (Zellermayer, 1996). There has been no research so far to see what the longer term effects of these changes in salience are for our relation to money,

and spending money, itself. Additionally, we have also postulated that the onset of using a new payment method can shift spending from a non-enabled account to the enabled account. This is again a possible explanation for the shift in increased spending we find, but there has been no research showing this shift to occur.

In line with the previous suggestion, there has been little to no research showing whether there is a difference between how people relate to money, and manage their personal finances, depending on which method they learned to manage money. Several younger generations learned about money not through using cash, but through e-money, online banking and holding payment cards, whereas older generations were taught about money through cash, the physical representation of money. Identifying the mechanisms which make for better personal finance management might be related to which payment method, physical or electronic, we grew up using, as a physical form of money does convey a different psychological construct than a non-physical form does (Trope and Liberman, 2010).

On the topic of longer term effects, we have attempted to see the effects of introducing a new payment method for an entire year after its introduction. It is possible that there is a habituation period, where the novelty of the payment method drives initial effects, but those effects subside after the consumer has had several months to become aware of, and adjust to, these effects. For example, in the first month the new payment method causes increased spending due to its ease of spending, an often mentioned feature of the contactless card. However, the consumer notices this, as the bank balance is surprisingly lower than expected, whereas the past expenditures made through contactless methods accumulate to a value that is higher than expected. It might be that this awareness is enough to counteract the effects of the payment method itself. Little is known about a possible habituation period for newer payment methods being introduced into the financial life of a consumer. However, findings such as those of MasterCard US (2011) and Trütsch (2014) showing increases in per expenditure spending as high as 30% are not numbers that can persist for long, without the consumer increasing their monetary means, adjusting their spending division, or accumulating debt. As such, we do think there is a likely habituation period for these methods, however, research has not yet confirmed this.

We would like to reiterate again the importance of having access to all the data of a consumer's financial dealings when researching their financial position, and changes in their financial position. We urge future researchers to only work on *complete* data sets (e.g. those from a consumer's main financial institution), to capture possible changes in financial situations.

4.6 Conclusion

We have shown there to be an effect of contactless payment methods on spending, cash usage, savings and a categorical change in spending, up to a year after its introduction. Most effects can be partially explained by the contactless active account becoming more prominent in usage, as indicated by an increase in credits and internal transfers. More research needs to be done to further our understanding of the relationship between spending, payment methods, how we manage our personal finances and how we relate to money as a concept. We urge researchers to exclusively work with data sets that capture the consumer's full financial situation to be able to see the full effects of a change in financial circumstance, such as the introduction of a new payment method.

Chapter 5

Mobile Payments: Salience vs. Simplicity

5.1 Introduction

The past few decades have seen an immense growth in payment options. Options currently range from cash to PIN-verified cards and from PIN-verified cards to contactless mobile devices. Banks and other financial institutions have striven to make the method of payment as easy and convenient as possible (Krol et al., 2016). Yet the ease of these payment methods might be a bigger issue than expected. Since the introduction of value-holding cards, society has moved towards being increasingly cashless.

When the credit and debit cards were introduced, it was seen as progress (Rosenberg, 2005). It is argued to be progress as it has been proven to be more convenient and safer than using cheques or cash, despite possibilities of card-hacking, cloning, fishing scams etc. (Angrisani, Foster, and Hitczenko, 2013). However, during the time of the introduction and uptake of PIN-verified cards, the effect of payment method on purchasing and expenditure was assumed to be non-existent. It was believed that the payment mechanism had no role to play in a rational, economic evaluation of a purchase opportunity. For example, whether an item is paid for by a debit card, cash or cheque (assuming no fees involved) should not alter the perception or experience of the price or product, as they remain the same. From this reasoning stems the argument that moving towards a cashless society is a step forward (Rosenberg, 2005).

However, as the PIN-verified cards increased their market share, research started to focus on their effect on expenditure and the purchasing experience. Currently there is substantial evidence suggesting that consumers who predominantly use both debit and credit cards overspend relative to those who do not (Feinberg, 1986; Hirschman, 1979;

Runnemark, Hedman, and Xiao, 2015; Soman, 2003; Tokunaga, 1993). Gross and Souleles (2002) have used the rather robust body of empirical evidence showing overspending in credit cards and have linked the cards to growing levels of debt within societies that promote their usage. This debt was argued to be driven not only by increased spending, but also a lessened awareness of spending, leading individuals to not correctly update their mental account balance and spend money “twice”. Predominant credit card usage has even been linked to impulse promotion and increased (unhealthy) impulsive behaviours (Thomas, Desai, and Seenivasan, 2011).

Although card usage exceeds that of cash in most of Europe, the popularity of cards is not a global phenomenon. Looking towards other countries and continents we see the surge of payment apps such as WeChat, Alipay, ApplePay and various other e-wallets (Statista, 2020b). Although the initial mobile payment revolution came from the East, the West is slowly catching on, predominantly relying on ApplePay, Android Pay, and traditional banks launching mobile payment platforms (Statista, 2020c). It remains to be seen how long it will take before mobile payment usage exceeds card usage, with mobile payments becoming the new normal.

A similar lack of information about the effect of debit and credit cards is now surrounding the introduction and widespread acceptance of mobile payments. The introduction of these payments can be seen as another step towards the cashless society envisioned by Rosenberg (2005). Figures from the UK Cards Association (2019) indicate that the growing popularity of mobile payment has accelerated the replacement of cash. In 2019, the UK saw 19.1% of its transactions being made through a mobile device, at the point of sale. As a European country, it is not in the lead, the Scandinavian countries, most notably Norway (25.8%), Sweden (36.2%) and Denmark (40.9%), are the European countries in which mobile payments are most prominent. In North America, we see that the US leads, having 29% of its transactions through mobile payments, followed by Canada with 26% of its transactions being mobile. The countries with the highest market penetration of mobile payments are in Asia: China leading with 81.1% of its transactions being through mobile payments, followed by India (37.6%) and South Korea (36.7%) (Statista, 2020d).

Despite mobile payment methods have been around for over a decade, little research has investigated its consequences on personal finance. Four studies by Huang and Savary (2018) showed that when using online mobile apps such as Venmo, there is an attenuation of the endowment effect. This effect was mainly driven by the increase in the participants’ willingness to pay when mobile payment methods were used, as compared to cash. The authors argued that this was due to the reduced salience of mobile payment methods. Research by Garrett et al. (2014) did show that there were strong associations between

mobile payment adoption and high cost debt (payday loans, auto-title loans), trouble with financial management (making ends meet), and credit card behaviour (taking cash advances and paying over the limit fees). The authors explained these results by suggesting that users of mobile payment technology were focused on convenience, and they might be prone to impulse spending. In addition, research by Meyll and Walter (2019) shows that the usage of mobile spending increases the likelihood of exhibiting costly credit card behaviours. Using a sample of over 25,000 US households from the 2015 National Financial Capability Survey (NFCS), the researchers find that mobile payment users are less financially literate and have higher levels of financial risk tolerance compared to non-users. When controlling for these two variables, the researchers find that using mobile payments is associated with a 4.9% increase in the likelihood of exhibiting costly credit card behaviour, which has been defined as only making the minimum payment, paying late fees or over the limit fees. Within the group of mobile payment users, those who use this method frequently are another 5% more likely to exhibit costly credit card behaviour compared to infrequent users. Meyll and Walter (2019) explain this increase in costly behaviour with the pain of paying (Zellermayer, 1996).

Closely linked to mobile phone payments are contactless (card) payments. Despite the form being different, a mobile payment follows the same mechanism as a contactless (card) payment and can be classified as such: the tapping of a device against the payment terminal at the point of sale, without additional verification through PIN or signature. Research on contactless card payments has shown a correlation between contactless usage and increased spending. MasterCard US (2011) found that per-transaction expenditure increased by 30% with their PayPass contactless cards introduced over a decade ago. Trütsch (2014) found that contactless cards resulted in higher spending at the point of sale compared to their non-contactless equivalents. This effect was 8.3% for credit cards and 10% for debit cards. See-To and Ngai (2019) found that the payment method significantly affected spending and awareness of spending, when comparing cash, credit card and contactless cards. Looking at single transactions within a Hong Kong mall, they found that less accurate expenditure recall led to increased willingness to spend, regardless of payment method. Research done in the UK showed that a sample of British students reported increased spending, reduced awareness of spending and feeling less in control of their finances with contactless payment (James, 2017). Given the similarity of the mechanism underlying both payment methods it is fathomable that the effects would be similar.

We do see indicators of contactless methods of payment being associated with increased spending, more frequent spending and a sense of decreased awareness and control over spending. These factors have been empirically linked to debt accumulation. We have

empirically verified these links, showing that the uptake of contactless led to increased spending, spending frequency, cash usage and savings in Chapter 5. In this chapter, we aim to see which of these findings hold true for mobile payments as well.

Our research contributes to the existing literature in the following ways: we extend the existing theories on payment methods to fit a relatively new payment method: mobile payments. Second, we use third party collected data to do so, rather than a survey based approach. Third, we use a large sample based in the UK, rather than the US. The advantage to doing so is that mobile payments have become normalised and popularised within the UK payment landscape, now accounting for at least 20 percent of transactions, whereas they have yet to do so within the US payment landscape. Fourth, we test for the effect of the onset of mobile payment usage on spending, fees and charges, debt, cash usage, and savings conjointly, rather than separately, as seen in the before studies, providing a clearer overview of the potentially wide-reaching effect of mobile payment methods.

5.2 Background

Payment methods have been shown to significantly affect personal finance, in a number of aspects. Research finds, when comparing credit cards to cash, that credit cards are associated with increased spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Soman, 2003; Tokunaga, 1993), worsened spending recall (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; Srivastava and Raghubir, 2002), decreased product attachment (Shah et al., 2016), reduced impulse control leading to more frequent spending (Omar et al., 2014; See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and debt accumulation (Gross and Souleles, 2002). However, these effects have been mainly established when comparing credit cards to cash. Research by Runnemark, Hedman, and Xiao (2015) found that debit cards were also associated with higher willingness to pay, when compared to cash. And a study by Shah et al. (2016) also looked at product connectivity comparing cash to debit cards, finding connectivity to be lower with the latter. Several theories have been proposed to explain these differences.

5.2.1 Pain of Paying

The dominant theory in explaining the difference between payment methods is that of the “pain of paying”, in which different methods of payment influence the way consumers feel about the payment (Zellermayer, 1996). When using cash, consumers experience a robust amount of negative feelings during the transactions. These negative feelings are invoked

by the physical handing over of the cash, the representation of value that cash signals and the concurrency of payment with the receiving of the good or service paid for. The reason these three aspects matter to the pain of paying is due to their influence on the ease and friction of the payment. Paying with cash is a long process, with the frictions of having enough cash, counting cash, handing it over, receiving some back etc., whereas paying by card has much less friction; there is no need for counting, nor exchanging hands. The card just gets swiped or tapped (in case of contactless), maybe a PIN needs to be entered. It is easier and faster. As a result, card payments are less painful.

So what is needed for a “painful” payment is physicality, value representation (transparency) and concurrency (Zellermayer, 1996). Different payment methods score differently on these criteria and the observed increase in spending when using credit card compared to cash, is then simply explained by different levels of pain. The more pain experienced, the less is spent. This simple statement seems to be supported by many studies, as they have found that spending and also willingness to spend is much higher using credit cards than cash (Prelec and Simester, 2001; Raghurir and Srivastava, 2008; Soman, 2003; Thomas, Desai, and Seenivasan, 2011).

The pain of paying focuses almost exclusively on spending, but has been used to explain effects of reduced spending awareness as well (See-To and Ngai, 2019; Srivastava and Raghurir, 2002). It is reduced spending awareness in which we are increasingly interested, as it is reduced awareness that has been linked to increased debt accumulation (Gross and Souleles, 2002). They propose that if people cannot recall their spending accurately, they will not be able to update their mental account balance. As such, there will be a change in the actual account balance, but not in the mental account with which the consumer keeps track of their spending on that specific account. This makes it possible for consumers to spend their money “twice” as explained by Gross and Souleles (2002). The consumer did not remember having spent money already and as such spends it again. This leads to people hitting their overdrafts and getting into debt on their real accounts, before they thought they would according to their mental accounts. As such, when mental accounting of this type is made more difficult through reducing a payment’s memorability or salience, for example by reducing the pain of paying, the likelihood of hitting overdraft increases.

In this field of research, mobile spending has flown under the radar. However, research by Pisani and Atalay (2018) has shown that payment with mobile devices and contactless (RFID-based) gadgets payments are experienced as less painful. As such, it is of societal importance to know whether this even easier and quicker method of payment fits within the pain of paying framework and can lead to higher debt accumulation through reduced awareness.

5.2.2 Multi-functionality

The pain of paying was proposed when most payment methods had one functionality, they could only be used as payment methods, they had no other function. However, the introduction of mobile payments changed this: mobile devices have multiple functions, of which one is being a payment method, making them multi-functional. This shift toward multi-functionality in payment modes is assumed to reduce payment salience and consequently decrease consumers' recall accuracy of past expenditures. This would relate to the salience of payments discussed in the previous sections. A mobile device is a hyper-multi-functional device, its payment function not being heralded as its main function. It is possible that this hyper-multi-functionality reduces the salience of the device as a payment method, and the individual transactions associated with it.

Research by Gafeeva, Hoelzl, and Roschk (2018) finds that recall accuracy is lower when using a single- or a multi-functional card as compared to cash. However, they also find that it is not the multi-functionality of the card that results in a higher recall error but the individual usage patterns: A higher usage frequency of the non-payment functions results in a higher recall error. Carrying this finding over to mobile spending, the main function of a mobile device not being payment, we expect there to be an effect of reduced salience compared to any other payment method, predominantly cash.

5.2.3 Mental and Real-time Accounting

We already mention that a mobile phone has more functions than just that of being a payment method. However, one of these functions is being a device to manage finances. Most individuals with a mobile phone practice online banking, and have their banking app, if not also a different financial management app, installed on their device. As such, the mobile device is both for paying and tracking payments. It is the first time in the history of payment methods that these two functions are merged.

From a mental accounting perspective this is ideal (Thaler, 1999). We have mentioned mental accounting before, as research has shown that reduced salience of payments makes it more difficult to track expenses correctly mentally, leading to spending "twice" and increasingly incurring debt (Gross and Souleles, 2002). However, with a mobile device that tracks the expense as it is made, the need for mental accounting diminishes, as the opening of one's banking app is enough to correctly update the amount of money spent, and the amount of money left, in one, or even multiple spending accounts. Moreover, payments through mobile phone are by default linked to a payment app, which needs to be installed on the device, that sends out a notification once a payment method. Initially

used as a means of immediately detecting theft and fraud, this also aids in making recall of the expenditure easier, and aiding correctly updating the mental account.

Research has looked into the usage of mobile devices as a way of changing spending behaviour, given that mobile devices do have the possibility to track spending. Research by Huebner, Fleisch, and Ilic (2020) looks into using the mobile device as a channel of personalised feedback interventions to reduce credit card spending. They show that increasing the salience of cashless payments through personalized feedback interventions helps people gain better control over their credit card spending. In addition, they use this app-based intervention to let people categorise their expenses as ordinary or exceptional, and split treatment groups into who gets feedback regarding which type of spend (none, ordinary, exceptional and both). They show that consumers require both an aggregated overview of all their spending, and feedback on both their ordinary and exceptional spending. The authors explicitly argue that the rehearsal of an individual transaction was not sufficient to nudge credit card users towards spending less. Instead, both the categorising of transactions and the aggregated feedback were necessary for participants to reduce their spending. Given that mobile devices do present consumers with the aggregated transactions, and do send notifications indicating past spending, it is possible that mobile payments are in fact more salient than card payments which do not possess this feature, and as a result may improve personal finance management.

The idea that mere representation of how much has been spent and how much is left (the account balance) is enough to change behaviour has been rejected before. Aforementioned research by Huebner, Fleisch, and Ilic (2020) has shown this to be true, but research by Pocheptsova Ghosh and Huang (2020) shows that mere presentation of the bank account balance has a positive effect on spending, in the sense that it increases spending, and increases the likelihood of consumers who actively use these personal financial management tools to hit overdraft. As a result of this rather surprising result, we also account for interaction with the personal finance management (from hereon PFM) tool and see whether it further exacerbates the effects of using mobile payments, or counteracts them. The representation of the balance of resources left (Pocheptsova Ghosh and Huang, 2020) and providing an overview of all transactions made (Huebner, Fleisch, and Ilic, 2020) are two very different approaches. Indeed, whereas the approach by Pocheptsova Ghosh and Huang (2020) shows the consumer how much is left to spend, the approach by Huebner, Fleisch, and Ilic (2020) reminds the consumer of how much has already been spent.

5.2.4 Competing Theories and Hypotheses

There are several theories outlined above making different predictions about the effect of mobile payment methods. According to the pain of paying (Zellermayer, 1996), transparency (Soman, 2001), and multi-functionality (Gafeeva, Hoelzl, and Roschk, 2018), mobile payments, due to their simplicity and general ease of usage have reduced salience. As it becomes easier to spend it also becomes easier to lose track of spending. This reduced salience should lead to increased spending, reduced spending awareness and generally worsened personal financial management. We call this the simplicity account.

However, at the same time, theories grounded in mental accounting (Thaler, 1999) argue that mobile payments should in fact be more salient, as the device itself tracks the payments, and provides users with direct feedback of their spend. In addition to the notification sent to check whether the payment was made by the mobile device owner, the mobile device can also provide more detailed information when users change the default settings of the app, as well as have continuous access to their online banking app via their mobile device, allowing them to see the total overview of their spending. As a result, spending should become more salient, leading to reduced spending, increased awareness and generally improved personal financial management. We call this the salience account.

The idea of having a payment method which can both increase simplicity and salience at the same time is novel. With other payment methods, the increase of simplicity and the reduction of salience have gone hand in hand. The latter following from the former. With mobile payments, this may not be the case due to its multi-functionality. As a result, we are testing these two accounts against each other. Table 5.1 provides the hypotheses made for each account. We can see that these accounts are contradictory in nature.

		Simplicity	Salience
Hypothesis 1	Number of Transactions	Increases	Decreases
Hypothesis 2	Spending	Increases	Decreases
Hypothesis 3	Overdraft Fees	Increases	Decreases
Hypothesis 4	Unsecured Debt	Increases	Decreases
Hypothesis 5	Cash Usage	Decreases	Increases
Hypothesis 6	Savings	Decrease	Increase
Hypothesis 7	Credit Card Debt	Increases	Decreases
Hypothesis 8	PFM Tool Usage	Decreases	Increases

Table 5.1: Table showing the different predictions made by the accounts of simplicity and salience.

5.3 Method

5.3.1 Data

We analyse data from a Financial Aggregator App in the UK. The data spans 2012 to 2020 and represents the data of just under 300,000 users. Users sign up for the Financial Aggregator App and link all of the accounts they would like to track via the app. Even if users stop using a specific account, data collection by the app only ceases when users explicitly remove the account from the app.

Users are identified by a unique identifier. Information on users includes the year of birth, gender, (anonymised) postal code, salary range (within 10k increments) upon first using the app, overdraft balance upon first using the app and their account references within the app. .

Each bank account tracked by the app is identified by a unique identifier. Information on accounts includes what type of account it is (savings, credit card, current, other), the account provider (bank), and the account balance.

Information at the transaction-level includes the amount debited or credited to the account, the date of the transaction, the type of transaction as classified by the user, the system and both the user and system. It is the latter that we use for identifying the spending categories we created. It also shows who the recipient or sender of the transaction is, but a lot of information here has been removed if there were internal transfers or transfers to bank accounts belonging to other individuals. Most importantly, we have access to the transaction description which is a single string often detailing the type of payment and all of the information mentioned above, with the exclusion of the private banking details of an individual.

5.3.2 Sample

Through the transaction description, we were able to identify which providers did and did not flag mobile payment methods. Our sample is derived from those providers who do flag mobile payments, excluding all the others. This leaves us with 15 different providers, and reduces our original sample size by one third (Table 5.2).

We also decided to only look at current accounts within our analysis. It is up to the users discretion how many accounts, and which type of account, they sign into the Financial Aggregator App to track. Most users did sign up at least one, or several current accounts, but numbers are much lower for the other types of accounts (credit card, savings, other). We believe that these users do own these types of accounts, but simply decided not to track them. As a result we do not have a complete picture of the changes that

happen between these accounts as a result of mobile payment usage, and decided to only focus on the current accounts. This restricts our sample further.

Further restrictions focused on the number of accounts held by an individual. The maximum number of current accounts held by an individual user was found to be 309. This number of current accounts does not signal that the user is only looking into their own personal finances. As a restrictive measure, we only looked at people with 5 current accounts or less. Just under 90% of users do not hold over 5 accounts and remained in our sample.

Next, we restricted ourselves further to only look at the users who started using mobile payments, at the point of sale. Using the detailed transaction descriptions we were able to derive whether the transaction was paid for using a mobile payment method in an offline environment. Each transaction that included the string “appleplay”, “samsung pay” or “google pay” with the exclusion of online payments, was flagged as “mobile”. From thereon, it could be established when mobile payments were first used with a specific current account, linked to a user. That date was then marked as its first usage. This date then became month 0 as a time reference point. Besides the user needing to have started using mobile payments, we also required them to have at least half a year of data before starting to use mobile payments, so six months before (-6) and to have at least half a year of data after starting to use mobile payments, so six months after (+6). It has to be mentioned that all of the analysis is relative to the starting point of using mobile payments. We were then left with 39,477 accounts of 18,664 users. Just under half these accounts were mobile payment activated.

As we wanted to have a complete picture of the user when starting to use mobile payments, we needed to ensure that a user holds more than one current account, one mobile activated and one not mobile activated. We filtered out all the users who only have one account registered and are left with a sample of 11,312 users with 32,125 accounts.

Our last restriction was to limit our data to only six months before and after the introduction of mobile payments. For each account we now hold only 13 months of data. This further reduced our observations and accounts, but not our users. After this step we balanced our sample, ensuring that they had data for all thirteen months, leaving us with 7,308 accounts and 3,224 users for our analysis. Due to the balancing, some accounts no longer appeared in the data, meaning not every user had an account in both data sets (the mobile account set and the non-mobile account set). Ensuring that users still held one mobile current account and at least one non-mobile current account we filtered out those that did not, and were left with a sample of 1,469 users with a total of 3,305 accounts, of which 1,469 were mobile and 1,836 were non-mobile. All of these reductions and there effect on the sample can be seen in Table 5.2.

	Number of Transactions	Number of Users	Number of Accounts
Total	67,643,3185	271,856	1,320,670
Providers who flag			
Mobile Payments	493,867,694	225,783	951,011
Current Accounts	401,113,408	212,987	463,125
No More Than Five			
Current Accounts	359,471,404	202,803	378,901
Exclusively Looking at			
Mobile Users	45,083,449	18,664	39,477
Users that Hold More			
Than One Account	32,598,894	11,312	32,125
Restricting to 1 Year	10,413,419	11,312	26,041
Unit of Observation			
Changed to per Month	207,116	11,312	26,041
Excluding 2020	195,207	9,228	23,539
Balanced Sample	122,506	4,385	10,028
Users that Hold			
Both Account Types	19,079	1,469	3,305

Table 5.2: Table showing the different sample restrictions and their effect on the sample size, measured in observations, number of users and number of accounts included in the sample.

5.3.3 Variables

Our main analysis entailed eleven dependent variables, measured on a per-month basis:

- Spending was measured in both volume and value. The volume was simply the *number of transactions* is simply the number of transactions in the month on this account. The *total monthly spend* was defined as all debits out of the account, that were not internal transfers between accounts, savings, investments or repayments.
- The *cost of overdraft fees* was created by flagging overdraft fees within the transaction description and the internal categorisation mechanism of the data. The debit amounts of money associated with this string were summed per month and indicate the cost of the overdraft fees per month. The *likelihood of incurring an overdraft fee* is measured as a binary dummy, 0 indicating the user did not incur an overdraft fee within that month, 1 indicating that they did.
- The *likelihood of incurring unsecured debt* was created by flagging several forms of unsecured debt, such as unsecured loans and payday loans, within the transaction description of the data and the internal categorisation mechanism. The credit

amounts of money associated with this string, such as receiving of the money associated with the loan, were summed per month. The likelihood of holding this type of debt is measured as a binary dummy, 0 indicating the user did not hold unsecured debt within that month, 1 indicating that they did.

- Cash usage was flagged by finding cash withdrawals within the transaction description and the internal categorisation mechanism of the data. Summing those frequencies, we arrive at the *number of cash transactions*. Using the debits associated with the cash withdrawals, we find how much cash was withdrawn that month, arriving at the *value of cash spending*.
- *Savings* were flagged by both looking into the transfers from the current account into accounts that were registered as savings accounts, as well as looking into the transfers into the current account from accounts that were registered as savings accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of savings, and calculate the difference between these. Positive coefficients means that more money was moved into the savings account(s) than money was taken out out of the savings account(s).
- *Credits* were flagged by both looking into the transfers from the current account into accounts that were registered as credit accounts, as well as looking into the transfers into the current account from credit card accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of the credit account, and calculate the difference between these. Positive coefficients means that more money was moved into the credit account(s) than money was taken out out of the credit account(s). Negative coefficients mean that the credit card debt is increasing.
- To account for account activity we also created two variables measuring the money coming into the account. *Credits* were flagged by looking into all the money being transferred into the account, without exclusions. These transfers would include income. To check for inter-account activity we look at *internal transfers*, which are a measure of all the money coming into the account for which we have no information - these are other accounts of the user for which information is removed for privacy reasons. Income is excluded from this measure.

With regards to the independent variables, we accounted for income of per month, measured in the total money going into the measured account (credits), excluding internal

transfers. As seen with spending, we looked at the distribution of income and exclude the bottom and top 5% to reduce outliers.

Additionally, we were interested in the effect of the PFM tool on the eleven dependent variables. We aimed to see whether interaction with the PFM tool had any additional benefits or disadvantages, as spending increasingly shifts towards the mobile device, now making it both a tracker and a payment method. The interaction with the PFM tool was measured on a login basis, where we looked at the number of logins per month as a measure of PFM tool usage. In total there were only three independent variables: mobile payment usage, PFM tool usage and income.

In addition to the main variables of interest outlined above, we also looked into several spending categories. Sixteen spending categories had been derived and classified from the data, using the internal categorisation mechanism, which followed the system's category guidelines and can be adjusted by the individual user as they see fit.

All eleven outcome variables were measures of personal finance management and we ran eleven separate fixed effects regressions using individual and time fixed effects. We included fixed effects for the user (as identified by the user identifier) and for time at the monthly level for the account-based analysis. We included fixed effects for the individual users and for time at the monthly level for the user-based analysis. Table 5.3 shows the summary statistics of the variables of interest, before and after mobile payments uptake.

5.3.4 Analysis

To establish the effect of the onset of mobile payments on personal finance management, we ran a set of eleven fixed effect regressions on our eleven dependent variables. Within our regressions we test for the effect of income, mobile payment usage and PFM tool usage, accounting for the fixed effects for both the individual and calendar time.

With regards to the time level, this is measured in the month of transaction. The month of transaction is a counting measure starting at "1", which represents the very first month in the data, which is January 2012. The last month in the data is month "105", which represents June 2020. We account for time effects as we expect there to be differences in the economic situation that are influencing how money is being spent. As table 5.1 has indicated, we excluded the year 2020 from our sample, as this is not a representative financial year.

With regards to the individual effects, we always fix our effects on the individual user. In Tables 5.4 and 5.5 we look at the mobile enabled accounts but account for the user fixed effects. It is the same for Table 5.6 where we look at the non-mobile enabled accounts. In Table 5.7 we look at all the accounts of the individual user, as clearly indicated in the

	Before Mobile			After Mobile		
	Mean	SD	Median	Mean	SD	Median
Number of Transactions	40	38.4	30	42.7	41.3	32
Spending (in £)	1,033	1,158	620	1,069	1,186	659
Cost of Overdraft (in £)	2.2	9.42	0	2.15	9.07	0
Number of Cash Transactions	1.54	2.78	1	1.42	2.58	0
Cash Spending (in £)	90.4	249	0	92.9	253	0
Savings (in £)	224	464	0	234	480	0
Credit Card Debt (in £)	-236	514	0	-245	527	0
Credits into Account (in £)	3,848	3,333	2,882	4,014	3,400	3,012
Internal Transfers (in £)	688	1,478	50	696	1,456	86.3
Income (in £)	2,340	2,650	1,550	2,440	2,700	1,660
Logins	1.36	4.27	0	1.79	4.76	0

Table 5.3: Table showing the summary statistics of the variables of interest for the sample of all of the payment accounts from the sample of 1,469 mobile users.

result section. We made the active choice of starting our analysis at the account level, rather than at the level of the individual user. We wanted to see whether the uptake of mobile payment methods on one account had effects on that account exclusively, or would have spillover effects into the personal finance management of the user in general, and would have effects on non-mobile active accounts as well. We are offering a complete and detailed picture of the effects of the onset of mobile payment usage on an account and individual user level.

5.4 Results

Looking at the total sample of 1,469 accounts using mobile payments, we find several trends in our eleven dependent variables, plus in our independent variable of PFM tool management, which we also decided to visualize as a result of mobile payment method uptake. Figure 5.1 shows these trends. Across all eleven outcome variables, we see considerable movement both before and after the introduction of mobile payments. For number of transactions, total monthly spend, overdraft (both as proportion and total cost), savings and credit card debt, we see that all tend to jump with the introduction

of mobile payments. For cash withdrawals, we see a decrease in the number of cash withdrawals, but not in its value, which seems to increase. The proportion of unsecured loans seems to decline, regardless of mobile payment usage. Credits into the account seem to be in an upward trajectory up to the point of first mobile payment usage, then flat line. Internal transfers do now show a consistent trend. Most interestingly, we see a continuous increase in PFM tool usage, which continues to increase after mobile payment introduction.

These graphs show us the general trends within the data. These trends do not account for individual and time effects. Table 5.4 does, by showing the results of the effect of mobile payment uptake on the nine dependent variables, as measured by the fixed effect regressions. Table 5.5 shows the effect of the onset of mobile payment usage on the sixteen different spending categories as defined by the app.

Looking at Table 5.4, we find support for the first hypothesis proposed by the simplicity account. The number of transactions per month increases significantly by 5.04, and the total monthly spend increases significantly by £55.56. Interestingly enough, this is more than the increase in exclusively mobile spending, which accounts for only £38.25. We find evidence in line with the salience account for hypothesis 2, predicting that overdraft fees would decrease as a result of mobile payment uptake, as the cost of overdraft fees increases, but not significantly so, and the likelihood of incurring an overdraft fee has significantly decreased by 1.5%. We do not find evidence to support our either account for our third hypothesis, there is no change in unsecured debt associated with mobile payment uptake. In line with the salience account we find that cash usage has increased in both the number of transactions (.08) and significantly increased in the value of cash being withdrawn (£6.26) supporting the fourth hypothesis of the salience account. Continuing to support the salience account, we find evidence supporting its fifth hypothesis, that mobile payments would increase savings. Savings have significantly increased by £35.40 after the introduction of mobile payment. Credit card debt, measured as repayments minus the money taken out on credit, decreases as well, meaning that less debt is being repaid, or more is being used. This is in line with prior research, as well as the simplicity account, however this effect is insignificant, as shown in Table 5.4.

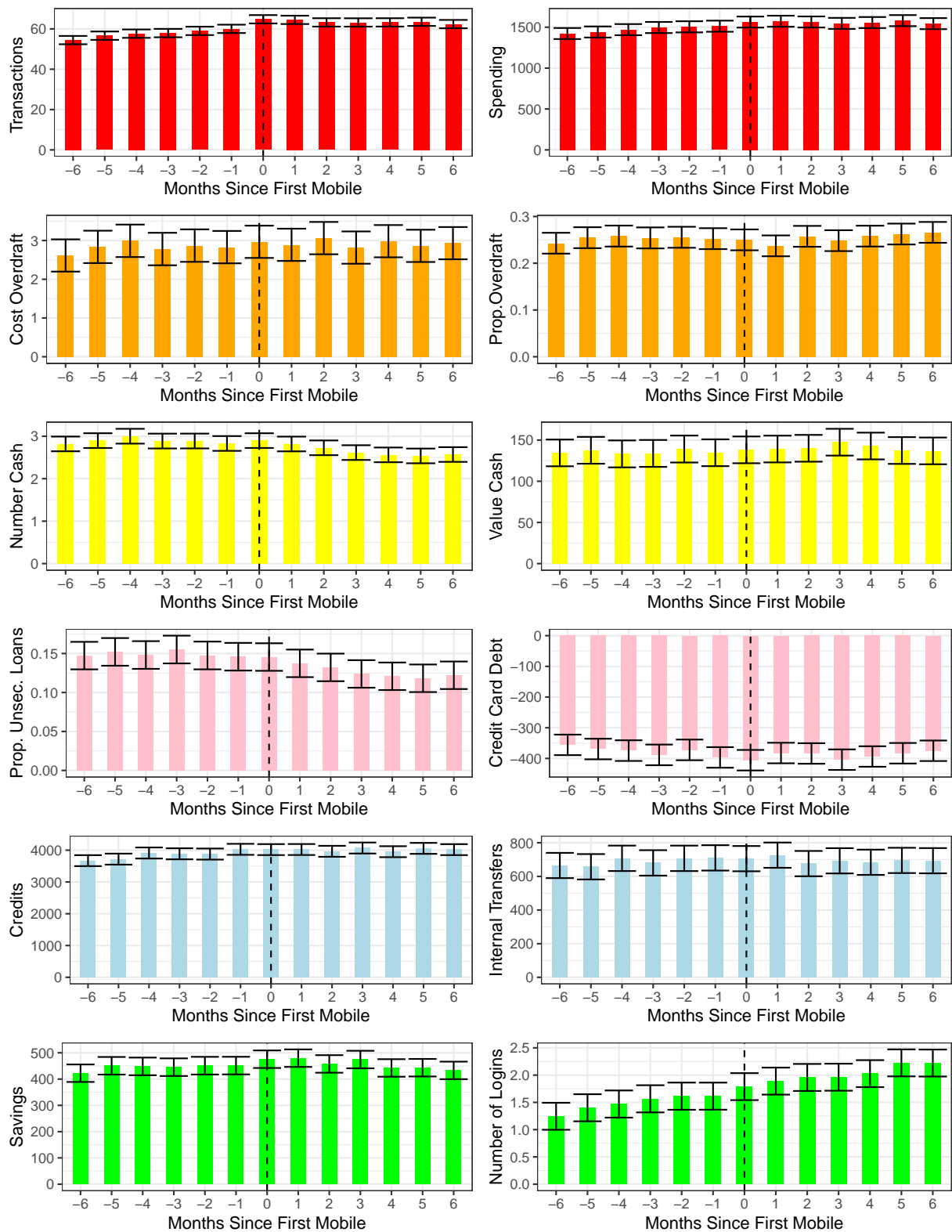


Figure 5.1: The effect of mobile payment usage six months before and six months after uptake on the mobile enabled accounts (Balanced sample of 1,469 accounts and 1,469 users). The stippled line refers to point zero, which is the month in which mobile payments were first used. Confidence intervals are at 95%.

Looking at the effect of the PFM tool usage, measured as the number of logins to the Financial Aggregator App app, we do not see the positive effect as predicted by supported mental accounting, neither do we see the negative effects as postulated by Pocheptsova Ghosh and Huang (2020). Our results are more in line with findings by Huebner, Fleisch, and Ilic (2020) who showed that mere balance display did not result in behavioural change. We also do not find an effect of PFM tool usage on any of our eleven dependent variables.

An increase in monthly spending of £55.56 is not a small increase for the average household. In addition to the significant increase in spending, we also have a significant increase in savings, totalling £90.96. We have controlled for income, and the resulting increase cannot be explained by an increase in monetary means. To explore this increase further we have looked at money moving into the account (Table 5.4). However, the onset of mobile usage does not seem to increase (internal) transfers directed into this account. To further explain the increase in both spending and savings, we have looked at how spending changes across categories (Table 5.5) as well as looked at the non-mobile accounts (Table 5.6) to potentially find a compensation mechanism.

Table 5.5 shows that mobile spending does have an effect on how money is divided across categories. We find that the uptake of mobile payments is associated with a significant increase in spending on the home, groceries, transport, going out, aesthetics and gifts. We also find that the uptake of mobile payments is associated with decreased spending on repayments, children, hobbies, and business, but none of these decreases are significant. We also find there to be no significant changes in spending on housing, insurance, health, gambling and one off and untagged spending, despite the latter being the biggest monetary change in spending. To clarify, untagged spending is spending for which we know nothing. The system hides most, if not all, information regarding this transaction. It is likely that this type of spending is largely based on internal transfers, as we are unable to see where the money is going, which is because of privacy protection.

Despite the slight differences in identifying of the monthly spending variable and the spending categories, what we do see is a general increase in spending across most spending categories with the onset of mobile payments usage. This general increase in spending is not explained by an increase in income, and has to be explained differently. We hypothesize that we are seeing a shift in how different payment accounts are being used. The onset of mobile payment usage making an account easier to use, and as such preferred. Research on payment methods, contactless methods specifically, did find a clear preference for using this particular method as it was quicker, safer and easier (Krol et al., 2016).

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Mobile Payment Usage	5.04*** (0.54)	55.56** (20.50)	0.13 (0.13)	-0.015* (0.01)	0.08 (0.06)	6.26* (3.03)	35.40*** (9.88)	-9.91 (11.19)	2.75 33.74	2.75 33.74
PFM Tool Usage	0.076 (0.11)	-0.07 (2.48)	-0.02 (0.02)	-0.001 (0.001)	0.01 (0.01)	0.24 (0.68)	0.18 (1.25)	-2.49 (1.34)	-0.29 (3.91)	-0.29 (3.91)
Income (in £100)	0.20*** (0.01)	12.40*** (0.59)	0.004 (0.003)	0.0001 (0.0001)	0.01*** (0.0009)	0.07 (0.07)	3.47*** (0.24)	-3.56*** (0.27)	103.83*** (0.96)	3.83*** (0.96)
R ²	0.82	0.74	0.70	0.70	0.69	0.89	0.75	0.68	0.90	0.45
Observations	18948	18948	18948	18948	18948	18948	18948	18948	18948	18948
Accounts	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469
Users	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5.4: The effect of the onset of mobile payment usage, PFM tool usage and income on the eleven dependent variables, for users that did use mobile payment, looking exclusively at their accounts that did have mobile payments activated on them. Includes fixed effects for user and calendar year-month. Balanced sample of 1,469 accounts of the 1,469 users.

	Housing	Home	Groceries	Insurance	Repayments	Health
Mobile Payment Usage	6.82 (3.98)	22.02*** (4.70)	14.61*** (2.99)	1.08 (1.02)	−4.78 (4.13)	0.56 (0.43)
PFM Tool Usage	0.64 (0.86)	−1.24* (0.58)	0.02 (0.37)	0.06 (0.11)	2.70*** (0.63)	−0.07 (0.04)
Income (in £100)	0.36*** (0.09)	0.79*** (0.08)	0.39*** (0.05)	0.10*** (0.02)	0.53*** (0.10)	0.02** (0.01)
R ²	0.85	0.78	0.79	0.70	0.74	0.51
Observations	18948	18948	18948	18948	18948	18948
Accounts	1469	1469	1469	1469	1469	1469
Users	1469	1469	1469	1469	1469	1469

	Transport	Children	Going Out	Hobby	Aesthetics	Gifts
Mobile Payment Usage	24.32* (11.42)	−0.10 (0.20)	11.66** (3.59)	−0.30 (0.75)	6.17*** (1.81)	0.37* (0.15)
PFM Tool Usage	1.69 (1.43)	0.01 (0.03)	−0.32 (0.38)	0.01 (0.07)	−0.18 (0.16)	−0.02 (0.02)
Income (in £100)	4.13*** (0.28)	0.01* (0.00)	0.65*** (0.06)	0.04*** (0.01)	0.26*** (0.03)	0.01*** (0.00)
R ²	0.67	0.47	0.59	0.50	0.53	0.37
Observations	18948	18948	18948	18948	18948	18948
Accounts	1469	1469	1469	1469	1469	1469
Users	1469	1469	1469	1469	1469	1469

	Business	One Off	Untagged	Gambling
Mobile Payment Usage	−0.08 (0.26)	0.05 (0.09)	33.24 (17.50)	0.30 (0.18)
PFM Tool Usage	0.02 (0.04)	−0.003 (0.01)	1.26 (2.38)	−0.05* (0.02)
Income (in £100)	0.01 (0.00)	0.004** (0.001)	10.14*** (0.49)	0.01** (0.003)
R ²	0.65	0.26	0.67	0.69
Observations	18948	18948	18948	18948
Accounts	1469	1469	1469	1469
Users	1469	1469	1469	1469

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5.5: The effect of mobile payment usage on the sixteen different spending categories, as identified by the system’s own tagging. Controlling for PFM tool usage and income. Includes fixed effects for user and calendar year-month. Balanced sample of 1,469 accounts.

To test whether the increase in spending on the mobile activated accounts is caused by an increase of account usage, at the expense of non-mobile activated accounts, we look exclusively at the non-mobile accounts. Running the same analysis as we did for Table 5.3, we find the results in Table 5.5. We find a different relationship between our dependent variables and the onset of mobile payment usage. We find that the uptake of mobile payments is associated with significantly less transactions made on the accounts without mobile payments. We also find decreases in spending, overdraft fees, savings, credit card debt repayment, credits into the account and internal transfers, although none of these terms are significant. Table 5.5 confirms our expectations of a compensation mechanism explaining the increases on the mobile payments enabled accounts, although it is not of the size originally hypothesized.

The decrease in spending and transactions we have found for non-mobile accounts does not fully explain the increase we find with the mobile active accounts. We have only explained a partial increase of spending on the mobile accounts, by compensating through spending on the non-mobile accounts. Users increase their spending on mobile accounts by £55.56, whereas they reduce spending on the non-mobile accounts explains £12.72. We also do not find an increase in credits into the account or internal transfers onto the mobile account, yet do find a reduced amount of both credits and internal transfers into the non-mobile account. Neither of these changes is significant.

To further investigate the effect of an account shift, we run an additional analysis on the overall user level. We run the same fixed effect analysis as we did before, but now accounting for all 3,305 accounts. The results of this analysis can be found in Table 5.7.

Looking at Table 5.7, we find that most effects initially associated with mobile payments (Table 5.4) continue to persist. We continue to see a significant increase in the number of transactions by 3.26, as well as a persistent increase in spending, cash value withdrawn and savings.

The effect on spending, when looking across all accounts, has lost significance. On a user level, the uptake of mobile payments is now associated with an increase in spending of £45.68. The effect of mobile payment uptake on overdraft fees, unsecured debt, credit card debt, and money moved into the account measured in credits and internal transfers is insignificant on the user level.

The decreases in coefficients when moving from an account to a user level do corroborate our hypothesis on there being a compensatory mechanism moving traffic to the mobile activated account, away from the non-mobile activated accounts.

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Loans (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Mobile Payment Usage	-1.42*** (0.38)	-12.72 (13.60)	-0.28 (0.17)	-0.01 (0.01)	0.002 (0.004)	-0.02 (0.03)	2.85 (1.72)	-2.60 (2.89)	-2.70 (5.64)	-24.30 (22.86)	-24.30 (22.86)
PFM Tool Usage	-0.0673 (0.05)	1.67 (1.52)	-0.03 (0.02)	-0.0001 (0.001)	0.001 (0.001)	0.001 (0.003)	0.15 (0.25)	0.41 (0.35)	-0.02 (0.75)	4.00 2.39	4.00 2.39
Income (in £100)	0.39*** (0.04)	14.53*** (0.84)	0.023* (0.01)	0.001* (0.0002)	0.001*** (0.0002)	0.01*** (0.001)	1.04*** (0.20)	1.11*** (0.16)	-4.08*** (0.35)	105.00*** (0.88)	5.00*** (0.88)
R ²	0.71	0.68	0.61	0.61	0.60	0.57	0.73	0.62	0.62	0.91	0.41
Observations	22907	22907	22907	22907	22907	22907	22907	22907	22907	22907	22907
Accounts	1836	1836	1836	1836	1836	1836	1836	1836	1836	1836	1836
Users	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5.6: The effect of the onset of mobile payment usage, PFM tool usage and income on the eleven dependent variables, for users that did use mobile payment, looking exclusively at their non-mobile accounts. Includes fixed effects for user and calendar year-month. Balanced sample of 1,836 accounts of the 1,469 users.

	Transactions (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Loans (prop.)	Cash (#)	Cash (£)	Savings (£)	Credit Card Debt (£)	Credits (£)	Transfers (£)
Mobile Payment Usage	3.26*** (0.66)	45.68 (27.26)	-0.20 (0.25)	-0.01 (0.01)	0.002 (0.01)	0.04 (0.07)	8.38* (3.79)	27.95** (10.46)	-14.05 (13.39)	-13.45 (80.24)	-31.13 (46.76)
PFM Tool Usage	-0.01 (0.05)	1.46 (1.26)	-0.02 (0.01)	-0.004 (0.0004)	0.005 (0.0003)	0.005 (0.003)	0.24 (0.28)	0.16 (0.54)	-1.26 (0.65)	0.23 (4.07)	0.54 (2.50)
Income (in £100)	0.19*** (0.01)	11.33*** (0.54)	0.01* (0.003)	0.0001 (0.0001)	0.0004*** (0.0001)	0.01*** (0.0008)	0.10 (0.07)	2.31*** (0.17)	-2.91*** (0.24)	74.54*** (1.61)	10.42*** (0.81)
R ²	0.83	0.75	0.75	0.71	0.72	0.71	0.89	0.76	0.68	0.70	0.49
Observations	18948	18948	18948	18948	18948	18948	18948	18948	18948	18948	18948
Users	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469	1469

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5.7: The effect of the onset of mobile payment usage, PFM tool usage and income on the eleven dependent variables, for users that use mobile payments, looking at all their registered accounts. Includes fixed effects for user and calendar year-month. Balanced sample of 3,305 accounts of the 1,469 users.

Lastly, looking at PFM tool usage, we continue to see no effects of logging into the app on personal finance management, neither on the account level (Tables 5.4-5.6) or the user level (Table 5.7). This is largely in line with findings by Huebner, Fleisch, and Ilic (2020) who showed that mere display of balances and budgets is not enough to change behaviour.

5.5 Discussion

5.5.1 Findings

We tested two different accounts on the effects of mobile payments of personal finance management, simplicity and salience, and found that neither theory fully accounts for the effects we find. We will discuss each in turn.

Spending

Initially, we find that mobile payment methods do significantly increase spending on the mobile enabled account, in both volume and value, indicating their alignment with theories such as the pain of paying and the simplicity account. The payment method is less physical, does not require an exchange and is quick and easy. It only requires a tap for the payment to go through. As such, the payment method does fit within the account of simplicity.

What is more interesting than mobile spending itself going up, is that the increase in spending which is caused by mobile payment usage cannot fully be explained by the spending done through mobile payment methods exclusively. Mobile spending only accounts for £38.25, whereas total monthly spending increases by £55.56, a difference of £17.31.

Having looked further into the increase in spending, which could not be explained as a wealth effect as we also controlled for income, we find that the increase is partially driven by taking usage away from other accounts, which are not using mobile payments. We find that the onset of mobile payments on one account, directs attention and usage towards this account, away from the other accounts of the user which do not have mobile payments associated with them. Indeed, when looking at non-mobile accounts, of which the user tends to hold slightly more than they do for mobile accounts, we find a decrease in spending and a significant decrease in the number of transactions being made on these accounts. Finally, when looking at users who have both types of accounts registered with

the app, we do continue to find a significant increase in the number of transactions, in line with the simplicity account, but the increase in spending has become insignificant.

Debt

The link between mobile payments and debt, measured in overdraft fees and short-term unsecured debt, as defined by unsecured loans and payday loans, is more complicated. The relationship between overdraft fees and mobile is partially negative, significantly reducing by 1.5% with the uptake of mobile payments on the mobile enabled account. When looking at accounts that do not have mobile payments enabled, we see that overdraft fee cost and occurrence decreases, but these numbers are small and insignificant. When shifting our view from the account perspective to the user perspective, we find that these opposite trends partially negate each other. Mobile payments continue to have a small negative impact on the cost and likelihood of incurring overdraft fees, but remains insignificant throughout, indicating that the onset of mobile payment usage does not change people's control of their immediate spending, and their accurate updating of their remaining balance, otherwise they would be receiving overdraft fees. This is contrary to previous research, especially that by James (2017), who found that UK students felt less in control of their finances when using easier payment methods such as contactless, and felt as if they were less aware of their spending. This finding rejects the simplicity account and supports the salience account.

Looking at the second form of debt, which includes unsecured loans such as payday loans, we do not find a significant increase in the likelihood of having this type of debt. This does seem to indicate that the increased spending we find with mobile payments does not take a toll on personal finance to the extent where taking on debt, in the form of a loan, is found to be a desirable option. We do not find a significant change in debt on non-mobile accounts either, nor do we find a significant change in debt when taking the user as our unit of observation. As such, our research does not support findings by Garrett et al. (2014) who found that mobile payment users were more likely to hold forms of high cost debt, such as payday loans. It has to be mentioned, however, that insufficient financial resources is not enough to increase short-term or unsecured debt uptake. A confounding variable which should be taken into account here is the availability of such loans to the consumer. Our data does not allow us to account for this.

Our results with regards to overdraft fees and unsecured short-term debt show support for the salience account, as we find no significant increase on either, and rather find a significant decrease in overdraft fees on the mobile enabled accounts. This puts an interesting spin on previous research which indicated that easier payment methods lead

users to feel like they were less in control of their finances (James, 2017). Despite their perception of losing control, we do not find proof of mobile payment users actively doing so.

Cash Usage

The relationship between mobile payment usage and cash usage is the opposite from predicted by the simplicity account, or by the general progression of payment methods (Rosenberg, 2005). Mobile payment uptake leads to an increase in cash usage, both in volume and value, only the latter increasing significantly, by £6.26. This number might not be of a great magnitude, but given that cash has often been heralded as a “budgeting tool” and might continue to be used as such, whether people felt that mobile payment transactions were not providing them with the same restraints, or not (Doyle et al., 2017).

The initial excitement at this finding persists as we find that the increase in cash we find on the accounts that do use mobile payments is not an artifact of these accounts becoming more prominent in usage: when looking at non-mobile accounts, we see that cash usage increases in value, but this increase is not significant. Looking at the user level, we now see a larger significant increase in cash usage value of £8.38 and a marginal and non-significant increase in cash usage frequency. This finding supports the salience account of the effects of mobile payments on personal finance management.

Savings

We find the onset of mobile payment usage to be associated with significantly increased savings. Savings, or at least the difference between money transferred from the current account to a savings account and the money transferred from the savings account to the current account has significantly increased by £35.40. When looking on a user level, we continue to find a significant increase in savings of £27.95. This shows clear support for the salience account of mobile payments, showing that people become in fact better at their personal finance management through the usage of the device as a payment method, and the Financial Aggregator App.

Credit

Looking at credit card debt, or at least the difference between money transferred from the current account to a credit account and the money transferred from the credit account to the current account, we find a decrease of £9.91, looking at the mobile enabled accounts. This means that more credit card debt is being used than is being repaid. This number, however, is small and non-significant. Turning our eye towards the non-mobile accounts,

we do not find a significant change in credit usage either, although the number remains negative. When looking on a user level, we continue to find a non-significant change in credit, but this number continues to grow more negative, indicating increased credit card debt usage. This finding is contrary to research by Meyll and Walter (2019) who found that mobile payment users exhibit costly credit card behaviour, or findings by Garrett et al. (2014) who also found that mobile payment users were more likely to exhibit costly credit card behaviour. Their findings provide evidence for the simplicity account, our findings, however, contradict theirs, favouring the salience account.

Account Activity

Our last two dependent variables were measures of account activity: all the money credited into the account (credits), as well as the money manually transferred into the account from the user's other spending accounts (internal transfers). We find no significant increase in account activity on the mobile active account, nor do we find a significant decrease in activity on the non-mobile account. Although the coefficients for both credits and internal transfers on the non-mobile account would explain approximately half the increase in spending on the mobile accounts. Moreover, we do see a compensation mechanism at play with regards to spending, where spending on the mobile account is compensated by a decrease in spending on the non-mobile account. We see a similar change in savings, where changes on the non-mobile account partially explain the changes seen on the mobile account. This does signal a shift in account activity, where activity on the non-mobile account reduces and activity on the mobile account increases as a result of it. Our specific measures for this change in activity, however, do not reach levels of significance.

PFM Tool Usage

There was contradictory evidence on the possible effects of actively using a personal finance management tool. The intuitive expectation was that real time tracking of money spent and money remaining would help support mental accounting and make it more accurate, as a result making people better at managing their finances. Research by Huebner, Fleisch, and Ilic (2020) then showed that mere expenditure tracking was not enough to invoke actual behaviour change, which was then contradicted by Pocheptsova Ghosh and Huang (2020) who showed that people who used a PFM tool showing the account balance were more likely to spend more than the money they had left and as a result were more likely to hit their overdraft. The mechanism Pocheptsova Ghosh and Huang (2020) use for explaining this finding is that the remaining balance is used as an

anchor, and that this anchor functions as a number that most closely represents a goal of how much money is left to spend, with the motivation to hit zero.

Contrary to both intuition and research, we find no significant effects with regards to the PFM tool. We do not find any effects, whether looking at the account or at the user level. This finding supports the research conducted by Huebner, Fleisch, and Ilic (2020). We find this effect to hold true for both our general analyses as well as the effect of the PFM tool on the detailed spending categories. The only categories affected by PFM tool usage are housing, measured in rent and mortgage, which does significantly decrease when using a PFM tool, but this decrease is minimal. Repayments also increase significantly when using a PFM tool. It is possible that the user has become more aware of their outstanding debt through using the tool and as a result puts more money toward repaying it. This would further support theories of mental accounting, and the salience account.

5.5.2 Limitations

A point of contention that has to be mentioned is the nature of the sample we are using. There is reason to believe that those who install and use a Financial Aggregator App on their phone are potentially a non-representative sample within the population. It can be argued that they are either very financially interested and knowledgeable, using the app to their advantage, whereas it is equally possible that this is a sample that is financially impaired and is trying to make sense of their finances by using this app. A combination of these two assumptions is also possible, potentially cancelling each other out when looking at all of the data in aggregate. Looking at UK statistics, over 50% of people indicate to use a financial app at least once a month. So we feel comfortable that our sample is approximating the population.

Furthermore, although consumers do select which accounts they register themselves, our findings with regards to the number of current, savings and credit accounts held, after some exclusions outlined in Table 5.2, does approximate the statistics of the UK population as a whole. We find that a large number of consumers do have a credit and savings account registered within the app. Not all users have done so, but then not all UK residents hold all types of account in general: just over 60% hold credit cards, and just over 35% hold savings accounts (Statista, 2021b).

To fully ensure we had a complete picture of the effect of mobile payments, we decided to only look at users who could present us with a complete picture, holding both a mobile and a non-mobile account, significantly reducing our sample size. Second, we decided to first look on the account level, and present a detailed analysis of changes in personal

finance management there, before moving onto the user level. This type of analysis presented us with a more detailed picture, showing us what happened on the account level, for both mobile and non-mobile accounts, as well as the user level.

Lastly, a small limitation within our analysis is that there are a number of untagged transactions within the data. We have no information on these transactions, as compared to all the other transactions for which we do have all details. It is difficult to see what their increased spending means for the personal financial situation for both the account and the user. However, due to the removal of all information regarding these transactions, we strongly suspect these transactions are more likely to be internal transfers between the accounts of the user, rather than actual spends. As a result, this category does not impact spending.

5.5.3 Contribution

This research contributes to earlier empirical work in several ways. First, it shows that mobile payment methods do not fit the simplicity account, as proposed by theories such as the pain of paying, transparency and multi-functionality. Rather, we find more evidence to support the salience account, which shows that mobile payments, due to their notification and increased expenditure awareness, improves personal finance management.

Second, we show that the onset of a new payment method on an account changes how that account is used. Our results show that the use of mobile payments on one account direct more attention and financial dealings to this account, at the expense of accounts that do not make use of this newer payment method. There is no prior research showing that the onset of a new payment method on one account leads to increased usage of that account, at the expense of other accounts. This is an interesting finding as it could provide a new way for financial institutions to motivate their customers to predominantly use their accounts, by offering them novel ways of paying.

Third, this research is unique in its methodology. Most of the prior work reviewed made use of lab work or survey responses, whereas we look at third party data, tracking the expenditures of a user and their registered accounts throughout. This approach increases the external validity of our findings.

Fourth, we use a large sample based in the UK, rather than the US. As mentioned before, the advantage is that mobile payments have become normalised and popularised in the UK payment landscape, whereas this has not yet occurred to the same extent in the US.

Fifth, we provide an overview of the effect of one new payment method, mobile payments, on a multitude of variables, rather than exclusively focusing on one aspect such

as spending. We paint a more comprehensive and exhaustive effect of a potentially wide-reaching payment method. In addition, we have also been able to study its effects on both the account and user level, providing more detailed and in-depth findings.

Sixth, finding that the effect of mobile payments on debt occurrence, measured in overdraft fees, payday loans and other unsecured loans, is not as big as postulated by payment theories, or rather, is not present at all in these data, is a relief, given the level of societal acceptance of this payment method. It is also a relief that cash still has a fighting chance, given that a reductions in either volume and value were not of the magnitude expected, nor of the direction expected. Cash remains to be a commonly used method of payment, which is good, given its budget-friendly constraints.

Last, our findings hint at the existence of other spending accounts that are not captured within this data. On a methodological level we show the difficulty of doing research when not having access to all of the user's accounts and financial data. We do not discourage researchers from using data sets such as the one here, but we do strongly recommend working with more complete data sets, such as those from financial institutions (e.g. banks), preferably the user's main financial institution, to capture the whole picture of a user's financial situation.

5.5.4 Further research

In addition to our findings here, further research is warranted to study the effect of payment methods on how we manage our personal finances. Most research focuses on only one aspect (e.g. spending, debt accumulation). We have attempted to paint a more complete picture, and we encourage future research to dive deeper as well.

We have to go beyond the payment methods as they currently stand. Mobile payment methods are not the most recent payment method to be introduced, yet research on these methods is already scarce. Newer payment methods become available faster every day. We cast our eye expectantly towards online spending, and the use of cryptocurrency as well. It is important we also understand the effect of these payment methods on personal finance management, as it is especially the younger generations who start spending and managing their money using these methods. It also remains to be seen whether every new payment method introduced continues to reduce salience as was initially expected, or whether (increased) salience can be built into these newer methods, to the benefit of the consumer.

As newer payment methods become increasingly faster available, and the pandemic and lock-downs have shifted the majority of spending online, we need to gain a better understanding of how these shifts, in both methods and settings, change the perception of

money. Is it possible that the introduction of a “quick and easy” payment method changes how we feel about spending money? Or about how we relate to money in general? The pain of paying does indicate that as payments become easier and quicker, that they are less painful and less salient (Zellermayer, 1996). There has been no research so far to see what the longer term effects of these changes in salience are for our relation to money, and spending money, itself.

In line with the previous suggestion, there has been little to no research showing whether there is a difference between how people relate to money, and manage their personal finances, depending on which method they learned to manage money. Several younger generations learned about money not through using cash, but through e-money, online banking and holding payment cards, whereas older generations were taught about money through cash, the physical representation of money. Identifying the mechanisms which make for better personal finance management might be related to which payment method, physical or electronic, we grew up using, as a physical form of money does convey a different psychological construct than a non-physical form does (Trope and Liberman, 2010).

Additionally, we have shown that the onset of using a new payment method can shift spending from a non-enabled account to the enabled account. There has been no research showing this shift to occur, or why this shift would occur. This is both interesting from a theoretical perspective as well as a practical perspective. With regards to theory, further research is required to understand why this shift occurs. Is this a novelty effect? Or are there different factors that drive consumers to favour accounts with newer payment methods enabled? From a practical point of view, if there is a novelty effect, how can this be used to attract and maintain customers? These questions have not been addressed by research yet, but do apply themselves for both theoretical and practical application.

On the topic of longer term effects, we have attempted to see the effects of introducing a new payment method for a half a year after its introduction. It is possible that there is a habituation period, where the novelty of the payment method drives initial effects, but those effects subside after the consumer has had several months to become aware of, and adjust to, these effects. For example, in the first month the new payment method causes increased spending due to its ease of spending. However, the consumer notices this, as the bank balance is surprisingly lower than expected, and the past expenditures higher. It might be that this awareness is enough to counteract the effects of the payment method itself. Little is known about a possible habituation period for newer payment methods being introduced into the financial life of a consumer.

We would like to reiterate again the importance of having access to all the data of a consumer’s financial dealings when researching their financial position, and changes in

their financial position. We urge future researchers to only work on *complete* data sets (e.g. those from a consumer’s main financial institution), to capture possible changes in financial situations.

5.6 Conclusion

We have shown there to be an effect of mobile payment methods on spending, overdraft fees, cash usage, savings, account activity and how we spend money in different categories, when looking at the mobile payment account. Looking at the accounts that do not have mobile payments enabled on them, we find that the increases found on mobile accounts are largely driven by a shift in account activity towards the enabled accounts. On the overall user level, we only find a significant increase in the frequency of spending, not the value of spending. Overall, our results are in favour of the salience account, showing that the onset of mobile payment usage is associated with better or at least unaltered personal finance management. We are relieved to find that mobile payments do not seem to effect overall spending or costly debt behaviours as shown by previous research (Gafeeva, Hoelzl, and Roschk, 2018; Garrett et al., 2014; Meyll and Walter, 2019). However, there is much more research that needs to be done to further our understanding of the relationship between spending, payment methods and personal finance management, as well as how we relate to money as a concept.

Chapter 6

Are You Being Skewed Over? The Effect of Payment Distribution on Spending Estimation

6.1 Introduction

Before the introduction of plastic cards as a payment method, the dominant method of payment was cash. Cash was freely traded around, and expenses were limited to how much cash was on hand. At the end of the day, however much cash was left determined how much had been spent. The distribution featured larger and more consistent expenditures.

Now, things have changed. We have constant access to money, via our payment cards or our mobile devices. As such, we have seen a shift in how most expenses are made, and how they are tracked. People who have access to money, or simply have less of a limit on their spending, are more likely to impulse spend (Thomas, Desai, and Seenivasan, 2011). As such, they are more likely to buy morning coffees, eat lunch out, or take a more expensive Uber rather than wait for public transport. These impulse expenditures are often small, but they do add up. More importantly, they fill up a bank statement, both paper and online, with these smaller expenses, and make it increasingly difficult to identify the larger expenses such as rent, mortgage payments or insurance. This makes it more difficult to mentally and accurately keep track of expenditure: how much money has already been spent and how much is still left to spend. This shift in moving individual smaller expenses away from cash and onto cards and bank statements was initiated by credit and debit cards, but was even further exacerbated by the introduction of contactless payment methods, making the process of payment faster and more convenient (James, 2017; MasterCard US, 2011; Trütsch, 2014).

This move towards impulse spending through the increased availability of money has long been corroborated. Research on payment methods show that, credit card usage, as compared to cash usage, has been linked to increased spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Runnemark, Hedman, and Xiao, 2015; Soman, 2003; Tokunaga, 1993), less accurate expenditure recall (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; Srivastava and Raghubir, 2002), reduced impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and debt accumulation (Gross and Souleles, 2002). As impulse spends tend to be small in nature, the promotion of smaller expenditures by different payment methods is likely to lead to an increasingly more positively skewed spending distribution.

When looking into newer payment methods, such as contactless card payments or mobile phone payments (at the point of sale), we see a similar picture. Contactless cards have been found to increase expenditures by 30% per-transaction (MasterCard US, 2011). Trütsch (2014) found that contactless cards, both debit and credit, resulted in higher spending at the point of sale compared to their non-contactless equivalents. The increases being 10% for credit, and 8% for debit cards. Research by James (2017) interviewed a sample of British students who reported increased spending, reduced awareness of spending and feeling less in control of their finances when using contactless payment. See-To and Ngai (2019) found that the amount spent affected awareness of spending. Looking at single transactions, they found that less accurate expenditure recall led to increased willingness to spend, regardless of payment method used.

Similar results were obtained when looking into mobile phone payments. Research by Garrett et al. (2014) found strong associations between mobile payment adoption and high cost debt (payday loans, auto-title loans), trouble with financial management (making ends meet), and credit card behavior (taking cash advances and paying over the limit fees). The authors explained these results by suggesting that users of mobile payment technology were focused on convenience, and they might be prone to impulse spending. Research by Meyll and Walter (2019) finds that using mobile payments is associated with a 4.9% increase in the likelihood of exhibiting costly credit card behaviour, which has been defined as only making the minimum payment, paying late fees or over the limit fees. Within the group of mobile payment users, those who use this method frequently are another 5% more likely to exhibit costly credit card behaviour compared to infrequent users.

However, it is entirely possible that the role of payment method, although well established, indirectly rather than directly causes the results found. A large part of spending, and personal finance management as a result, relies on the perception and memory of the resources already used, and those that are left. A large part of managing one's finances is

accurately being able to track them, accurately memorising and estimating how much has already been spent, how much still has to be spent, and how much is left to spend. From a memory perspective, payment methods in and of themselves might not be the leading cause in increased spending, decreased accuracy of expenditure recall and increased debt occurrence. It might be the spending distribution, and how different payment methods change what this distribution looks like, causing the different behavioural outcomes.

Memory is a finite resource. It has been well established that individuals can hold up to 7 ± 2 items in their short-term memory. A very recent expenditure could make up one of these items, but if the expense is more complex in nature, £281.57 instead of the much easier to remember £300, it can qualify as a “chunk” of which people are able to hold 4 ± 1 in their working memory (Baddeley, 1994; Miller, 1956). Transitioning this to longer-term memory, rather than forgetting the event, would require repetition or a form of application; in this scenario the updating of the mental account balance, as seen with mental accounting (Thaler, 1985).

Mental accounting, or the accuracy of recall of expenditure, has been linked to both payment methods and personal finance management. Gross and Souleles (2002) found that those who spend with credit cards were more likely to get into debt, as they inaccurately tracked their mental balance, which ended up not matching their actual account balance, putting them into debt. Gross and Souleles predominantly explained this by forgetting expenditures and spending money “twice”; spending money that was thought to still be in the account, but had in fact already been spent. Srivastava and Raghubir (2002) also showed reduced accuracy of memory when using a credit card as compared to cash. This effect could, however, be reduced by splitting expenses into different categories, e.g. travel, education, clothes. But the effect of inaccuracy remained larger for credit cards than it did for cash. In addition, See-To and Ngai (2019) showed that the higher the inaccuracy was for recalling previous spending, the more likely the person was to spend more. It is never specifically mentioned whether this increased inaccuracy of recall favours underestimation rather than overestimation of previous expenditure, but it can be assumed from the context.

The importance of memory in personal finance management becomes quite clear. Without accuracy of memory of the previous expenditures, people are likely to spend more and more frequently, and as a result, be more likely to get into debt. This debt can take many forms, as seen before within the research on different payment methods. Debt can be credit card based, but can also be more costly, such as overdraft fees and payday loans. All the aforementioned are variables of interest.

The level of difficulty in memorising expenditures is not the only aspect that influences

the accuracy of recall and the effectiveness of retention. As mentioned before, short-term memory is a finite cognitive resource. When recent expenditures do not transition to longer-term memory, they fade out, become increasingly more difficult to recall (without direct prompts) and are forgotten. This process will make expenditure estimates, and the accurately updating of the mental account balance, increasingly more difficult, and inaccurate. This can be influenced by the sheer quantity of expenses to be remembered. As the number of transactions go up, there is more room for error, and difficulty to keep track of both expenses made and monetary resources left. In addition, as spending becomes more frequent, it becomes less salient. Short-term memory to longer-term memory transition favours novel and unpredicted, and as a result salient, events (Snyder, Blank, and Marsolek, 2008). Once something has become quite ordinary, common or often rehearsed, it loses salience, and is less likely to be committed to memory. Moreover, when moving more transactions to a singular place, such as a bank statement or an online banking app, the sheer volume of transactions might make it more difficult to get an accurate overview of the number of transactions, and the total spending they sum to. As a result, the sheer increase in transactions can have an influence on the accuracy of perception and recall of expenditure. Interestingly, most payment methods, as compared to cash, have been linked to increasing the frequency of spending (James, 2017; See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011).

Hypothesis 1 *As the number of transactions increases, so does the error of expenditure estimation. We expect people to underestimate their expenses, leading to increased spending and increased debt.*

Additionally, it is important to distinguish between the number of transactions and total spending. These two concepts are heavily correlated and previous literature often does not make a clear distinction between the two, or only mentions one without looking into the other. It is entirely possible that recall error increases as a result of the number of transactions increasing, but it may also simply do so as a function of the total spend. If people are always within a 10% margin of being within their actual expenditure when estimating, absolute estimation error will increase as total spending increases.

When looking at the payment method literature, most of the research has focused on increased spending, showing that credit card usage (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Soman, 2001; Thomas, Desai, and Seenivasan, 2011; Tokunaga, 1993), debit card usage (Runnemark, Hedman, and Xiao, 2015), contactless card usage (MasterCard US, 2011; See-To and Ngai, 2019; Trütsch, 2014) and mobile payment usage (Garrett et al., 2014), as compared to cash, led to higher expenditure. Most of these

payment methods have also been linked to higher debt occurrence (Gross and Souleles, 2002; Lee, Abdul-Rahman, and Kim, 2007; Meyll and Walter, 2019), indicating that the accuracy of memory needed for correct mental accounting might be reduced. Accuracy of spending recall also influences future spending (See-To and Ngai, 2019). As such, there might be a direct link between increased spending, reduced memory and debt occurrence.

In addition to these findings, research specifically looking at expenditure recall in grocery stores consistently finds that customers systematically underestimate the total value of their shopping baskets (Scheibehenne, 2019; Van Ittersum, Pennings, and Wansink, 2010). Both Scheibehenne (2019) and Van Ittersum, Pennings, and Wansink (2010) approached customers during their shopping, asking them to estimate the total of their shopping basket before checking out. They both found a tendency towards underestimation, regardless of the characteristics of the underlying distribution, such as modality, skew and kurtosis. Scheibehenne (2019) validated this results in the lab, by displaying sequences of 24 numbers, with varying totals and underlying distributions to 40 participants, and found a general tendency towards underestimation of the total of the sequences, with again, no effect of the underlying distribution characteristics. He also found that the level of underestimation increased for larger sums, in line with our predictions and previous findings of similar patterns of underestimation with respect to the perception of numerals in general (Dehaene, 2011) and in a consumer context in particular (Van Ittersum, Pennings, and Wansink, 2010). In addition to Scheibehenne (2019) finding an effect of total but not of the underlying distribution, he also found that underestimation did not depend on the underlying frequency distribution, a finding which holds for both studies. This goes against our predictions which is based on previous empirical and theoretical support. However, there is previous research that also did not find such a relationship when information was presented sequentially (Hutchinson, Wilke, and Todd, 2008). Overall, this research does point at a clear relationship between the total value of a distribution and the error of estimating its total.

Hypothesis 2 *As total spending increases, so does the error of expenditure estimation. We expect people to underestimate their expenses, continue to increase their spending and increase their debt.*

The use of newer payment methods has been shown to lead to different spending patterns, giving way to smaller, impulse spends (Thomas, Desai, and Seenivasan, 2011). This does not merely affect the spending distribution by lowering the average-per-item-spend and adding more items to the distribution, it also increased the standard deviation of the distribution. The lower bound is being moved further down, towards zero, assuming that

most impulse spends are small in nature (e.g. an additional coffee to-go) rather than large spends at the top of one's disposable income. By also reducing the average-per-item spend, it is possible that the increased standard deviation of the spending distribution changes the way the true mean, or the true total of the distribution, is perceived. In the case of increasingly using methods such as contactless, and the presumed adding of smaller expenditures to the original spending distribution, we expect the perceived mean and total to be lower than the true mean and total.

Research by Brusovansky, Vanunu, and Usher (2019) shows that the perception of the mean of a distribution changes how people judge that distribution; favourably or not. In their experiment, participants were presented with rapid numerical sequences representing performances, class feedback, or rewards, which had to be used to rate the Hall of Fame eligibility of basketball players, or their liking of athletes, lecturers or slot-machines. Brusovansky, Vanunu, and Usher (2019) tested for the applicability of several models such as averaging, summation and the Peak-End heuristic, but found that averaging type models accounted best for participants' preferences. This finding supports the argument that a change in distribution, whereby the mean, and as a result the standard deviation, are changed will have an effect on peoples' perception of the distribution, and their estimated value of said distribution.

Hypothesis 3 *As the spending distributions has an increasingly larger standard deviation, the error of expenditure estimation increases. We expect people to underestimate their expenses, increase their spending and increase their debt.*

As seen with the number of transactions and total spending, there might be a multicollinear relationship that is often not explored. In addition to the standard deviation changing, so does the shape of the distribution of spending: its skew. A distribution in which small expenditures occur most frequently, or at least more frequently, with few larger expenditures is referred to as a positively skewed distribution. In this type of distribution the median is smaller than the mean. As the median reflects the value exactly in the middle of the distribution, it is likely that people will judge this as the mean, and underestimate the mean, and potentially underestimate the total value of the distribution. With regards to spending, this means they underestimate their total spending, leading to financial management in the way of hitting overdraft or incurring debt, as a result of this. Moreover, due to the sheer volume of small, potentially not salient expenditures (Thomas, Desai, and Seenivasan, 2011; Zellermayer, 1996), it is likely that people forget some expenditures, even further fuelling the underestimation of their total expenditure.

In contrast to the positively skewed distribution stands the negatively skewed distribution. This is a distribution in which larger expenditures occur most frequently, with fewer small expenditures occurring. In this type of distribution the median is larger than the mean. As the median reflects the middle expenditure, it is likely that people will judge this as the mean, and overestimate the mean, and potentially overestimate the total value of the distribution. With regards to spending, this means they overestimate their total spending. Moreover, due to the sheer volume of larger expenditures, which are judged as being more salient it is likely that people are quite aware of their expenditures. This can further fuel the overestimation of their total expenditure, or undo some of the initial underestimating often associated with expenditure recall (Scheibehenne, 2019; Van Ittersum, Pennings, and Wansink, 2010). Regardless, as contrasted to those experiencing the positively skewed distribution, those with negatively skewed distributions of spending are likely to either be quite accurate in estimating the total of their spending or are likely to overestimate the total of their spending. As a result, they are less likely to get into forms of debt associated with spending beyond one's means.

Despite our assumption that negatively skewed distributions would be more beneficial from a consumer perspective, most consumers are likely to experience positively skewed distributions rather than negatively skewed distributions. Most consumers have a few larger expenses such as rent/mortgage, healthcare, insurance, vehicle maintenance or education fees. These fees often occur on a monthly basis. More frequently occurring are grocery shops and eating out, which are often smaller expenditures. From there, the most frequent occurring expenditures are much smaller, such as the aforementioned morning coffees and lunches-to-go. With constant access to money, it is very easy to spend a couple of pounds per day.

Although most people will be exposed to a positively skewed distribution, research on skew shows that people have a strong preference for negatively skewed distributions. Tripp and Brown (2016) showed that participants when presented with a wage payment distribution task had a clear preference for receiving a set of negatively skewed wage payments, rather than a set of positively skewed wage payments, despite the mean and total value of these payments being the same. The authors explain this by emphasizing that within a negatively skewed distribution the larger values (as relative to the other values in the same distribution) are seen more often and as such might influence the participants' perception of the total value of the distribution. However, they did not test for the actual perception of the distribution so this remains conjecture. This study was a replication of Parducci (1968) who also found that the average satisfaction with individual payments was higher for negatively skewed sequences.

In addition, estimation accuracy for a sequence of numbers may also depend on the

shape of the underlying frequency distribution. Experimental evidence from research on risky choices indicates that preferences critically depend on the distribution of values that people experienced in the past (Stewart, 2009). Likewise, grocery shoppers can be influenced by the skew of product prices over time (Niedrich et al., 2009). Such patterns can be explained by several theoretical accounts including the decision by sampling theory (Stewart, 2009) and the range–frequency model (Parducci, 1965), and they align with early research on perception showing that negatively skewed distributions lead to lower mean estimates compared to positively skewed distributions (Parducci, Thaler, and Anderson, 1968).

Hypothesis 4 *As the spending distribution becomes increasingly positively skewed, the error of expenditure estimation increases. We expect people to underestimate their expenses, increase their spending and increase their debt.*

We propose to test these four hypotheses by conducting two studies. First, we will analyse the effects of the number of transactions, spending, standard deviation and skew by analysing their effect on nine measures of personal finance management. The measures of personal finance we are interested in are the frequency and value of spending, overdraft, unsecured debt (payday, credit card), cash usage and savings. We aim to test our hypotheses by using a 10% random sample from a transaction data set from a Financial Aggregator App based in the UK. This approach will give us proof of concept of these expected results, as well as provide our results with high external validity. As the hypotheses indicate, we expect an increase in all four independent variables (the number of transactions, total spending, standard deviation, skew) to be associated with an increase in spending, overdraft occurrence, debt usage and a reduction in savings. All signs of a reduced ability to manage one’s personal finances.

Second, we will conduct an online experiment, presenting participants with 20 randomly selected numerical sequences, varying in the number of stimuli, total, skew and standard deviation. Participants will be asked to estimate the total of the distributions to the best of their ability, establishing a direct relationship between our four variables of interest and accuracy of estimation of a spending distribution. This approach will allow us to make causal claims. Again, we hypothesize that an increase in transactions (stimuli), total, standard deviation, and skew will lead to underestimation of the total.

6.2 Study 1: Financial Aggregator App Data

6.2.1 Data

We analyse data from a Financial Aggregator App based in the UK for the time period between January 2012 until June 2020. Using a random 10% sample of this data, we are presented with 26,982 users residing in the UK, with 64.8 million transactions. Users sign up for the app and link all of the accounts they would like to track via the app. Even if users stop using a bank account, data collection by the Financial Aggregator App only ceases when users explicitly remove a bank account from the app.

Users are identified by a unique identifier. Information on users includes the year of birth, gender, (anonymised) postal code, salary range (within 10k increments) upon first using the app, overdraft balance upon first using the app and their account references within the app.

Each bank account tracked by the app is identified by a unique identifier. Information on accounts includes what type of account it is (savings, credit card, current, other), the account provider (bank), and the account balance.

Information at the transaction-level includes the amount debited or credited to the account, the date of the transaction, the type of transaction as classified by the user and the app itself and who the recipient or sender of the transaction is. Most importantly, we have access to the transaction description which is a single string often detailing the type of payment.

6.2.2 Sample

We have identified 26,982 users and 129,348 accounts from the original 10% sample. However, we impose further restrictions on this sample before we start our analysis, or create our variables. We decided to only look at current accounts, as these are accounts that have the level of spending and activity on them as we required. This reduced our sample size to 25,448 users with 60,410 accounts.

We further restricted the number of accounts held by an individual. The maximum number of current accounts held by an individual user was found to be 128. This number of current accounts does not signal that the user is only looking into their own personal finances. As a restrictive measure, we only looked at people with 5 current accounts or less, reducing our sample to 23,927 users and 47,727 accounts.

For our analysis we decided to exclusively look at the account level. We created our variables, as indicated below, and aggregated them per month. After this aggregation we

filtered out the year 2020, as it was a non-representative year, and are left with 47,312 accounts.

Furthermore, we decided to exclusively look at accounts that were being actively used. We defined active usage as having at least 10 transactions per month on the account. This further reduced our sample to holding 38,407 accounts. This is the sample we used for our analysis.

6.2.3 Variables

Our analysis entailed nine dependent variables. All variables expressed in pounds (£) have been winsorized by 5% on both sides. All variables are measured on a per-month basis, for the account.

- Spending was measured in both volume and value. The volume of spending is simply the *number of transactions* in the month on this account. The value of spending, the *total monthly spend*, was defined as all debits out of the account, that were not internal transfers between accounts, savings, investments or repayments.
- The *cost of overdraft fees* was created by flagging overdraft fees within the transaction description and the internal categorisation mechanism of the app. The debit amounts of money associated with this string were summed per month and indicate the cost of the overdraft fees per month. The *likelihood of incurring an overdraft fee* is measured as a binary dummy, 0 indicating the user did not incur an overdraft fee within that month, 1 indicating that they did.
- The *likelihood of incurring unsecured debt* was created by flagging several forms of unsecured debt, such as unsecured loans and payday loans, within the transaction description of the data and the internal categorisation mechanism. The credit amounts of money associated with this string, such as receiving of the money associated with the loan, were summed per month. The likelihood of holding this type of debt is measured as a binary dummy, 0 indicating the user did not hold unsecured debt within that month, 1 indicating that they did.
- Cash usage was flagged by finding cash withdrawals within the transaction description and the internal categorisation mechanism of the app. Summing those frequencies, we arrived at the *number of cash withdrawals*. Using the debits associated with the cash withdrawals, we find how much cash was withdrawn that month, arriving at the *value of cash withdrawals*.

- *Savings* were flagged by both looking into the transfers from the current account into accounts that were registered as savings accounts, as well as looking into the transfers into the current account from accounts that were registered as savings accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of savings, and calculate the difference between these. Positive coefficients means that more money was moved into the savings account(s) than money was taken out out of the savings account(s).
- *Credits* were flagged by both looking into the transfers from the current account into accounts that were registered as credit accounts, as well as looking into the transfers into the current account from credit card accounts, through either the transaction description or the internal categorisation mechanism. We can see how much money is moved in and out of the credit account, and calculate the difference between these. Positive coefficients means that more money was moved into the credit account(s) than money was taken out out of the credit account(s). Negative coefficients mean that the credit card debt is increasing.

With regards to the independent variables, we looked at our four variables of interest: number of transactions, total spending, standard deviation and skew. The former two were measured in the same we as explained above, when addressed as dependent variables. Standard deviation was measured as the standard deviation of monthly spending. Skew was measured as the skew of the monthly spending distribution. Lastly, we accounted for the income of the app users per month as well, measured in the total money going into the measured account, filtering out internal transfers. In total there were five independent variables: number of transactions, total spending, standard deviation, skew and income.

6.2.4 Analysis

All nine outcome variables were measures of personal finance management and we ran nine separate fixed effects regressions using individual and time fixed effects. We included separate fixed effects for the accounts (as identified by the account reference) and for time at the monthly level. Table 6.1 shows the summary statistics of the dependent variables, giving context to the coefficients presented in Table 6.2.

	Minimum	25%	Median	75%	Maximum	Mean	SD
Number of Transactions	10	27	50	80	2113	58.7	41.3
Number of Spending Transactions	0	25	55	87	3167	62.0	50.3
Spending (in £)	90	501	1069	1978	4916	1457	1287
Cost of Overdraft (in £)	0	0	0	0	18	1.71	4.61
Number of Cash Withdrawals	0	0	0	1	52	1.21	2.71
Cash Value Withdrawn (in £)	0	0	0	40	360	48.1	99.1
Credit Card Debt (in £)	-2322	-278	0	0	0	-321	628
Savings (in £)	0	0	0	86	1077	134	287
Income (in £100)	0.47	11.7	22.4	39.3	110	30.5	28.0
Standard Deviation	0	59.6	122	264	1024	222	258
Skew	1.00	2.33	3.58	5.13	7.74	3.84	1.89

Table 6.1: The summary statistics of the variables of interest.

6.2.5 Results

Looking at the nine fixed effect regressions (Table 6.2), we see a mixed picture. We find support for our first hypothesis: we find that an increase in the number of transactions is associated with a significant increase in spending, which makes intuitive sense, as well as a significant increase in the cost and proportions of overdraft fees and the increased proportions of unsecured loans, both proxies for debt accumulation. The number of transactions is also associated with a significant increase in the value of cash withdrawals, as well as savings. However, both these effects are marginal. There is no significant association between the number of transactions and credit card debt.

For our second hypothesis, the effect of the total of the distribution, in this case measured in the amount of monthly spending, we find that the total of the distribution is associated with a significant increase in the number of transactions, which was again to be expected. However, increases in the total are also associated with significant reductions in cost and likelihood of overdraft fees, counter to our hypothesis. The opposite is true for unsecured loans, where increased spending is associated with a significant increase in the likelihood of having an unsecured loan. Increased spending is also associated with significant increases in the frequency of cash withdrawn, as well as significantly

increasing savings and credit card debt being used. Negative coefficients for credit card debt meaning that the account is making use of more credit. Again, the magnitude of the latter three findings (cash, credit, savings) is marginal. We find partial support for our second hypothesis.

Looking at hypothesis 3, the effect of standard deviation, measured in the standard deviation of the spending distribution, we find an increase in standard deviation to be associated with significant decreases in the number of transactions, the likelihood of using unsecured loans, cash withdrawals and credit card debt. An increase in the standard deviation is also associated with a significant increase in spending, which is part of how it is calculated, as well as significantly increasing savings. We do find partial support for our third hypothesis, although the effect of the standard deviation on any of these variables is, at best, marginal.

Looking at hypothesis 4, the effect of skew, we find that the skew of the distribution is associated with a significantly higher number of transactions and a significant increase in spending by over £20, the latter being a characteristic of how skew is calculated. We also find that an increasingly positively skewed spending distribution is associated with a significant increase in overdraft, both in cost and likelihood. More interestingly, an increase in skew is also associated with significantly less credit card debt, as well as significantly reduced savings. The increase in overdraft occurrence, as well as the decrease in savings are indicators of a reduced ability to manage one's finances, supporting our fourth hypothesis.

We conclude that our results are largely in line with our predictions. Increasing the number of transactions is associated with an increase in spending and all forms of debt, in line with hypothesis 1. Increasing the total of the spending distribution is associated with an increase the number of transactions and the number of cash withdrawals, but negatively impacts overdraft usage, but does stimulate unsecured loan usage, which only partially supports the second hypothesis. Increasing the standard deviation of the distribution is associated with less transactions and less debt, going against our initial predictions in the form of hypothesis 3. Increasing the skew of the spending distribution is associated with the largest effects, showing strong support for the fourth hypothesis, with increases in spending, spending frequency, overdraft, unsecured loans and a decrease in savings.

	Spending (#)	Spending (£)	Overdraft (£)	Overdraft (prop.)	Unsecured Debt (prop.)	Cash (#)	Cash (£)	Credit Debt (£)	Savings (£)
Number of Transactions		11.05*** (0.34)	0.02*** (0.002)	0.0007*** (0.00004)	0.0001*** (0.00002)		0.38*** (0.02)	-0.03 (0.24)	2.30*** (0.55)
Spending	0.002*** (0.00004)		-0.0001*** (0.00001)	-0.000005*** (0.0000002)	0.000001*** (0.0000001)	0.00003*** (0.000002)		-0.15*** (0.004)	0.09*** (0.02)
Standard Deviation	-0.001*** (0.0001)	0.01*** (0.002)	0.000003 (0.00001)	-0.00000001 (0.0000001)	-0.00000003*** (0.0000001)	-0.00002*** (0.00000)	-0.00001 (0.0001)	0.03** (0.01)	0.24*** (0.07)
Skewness	6.93*** (0.05)	23.69*** (2.60)	0.04** (0.02)	0.003*** (0.0004)	0.00004 (0.0002)	0.11*** (0.003)	-0.06 (0.13)	14.27*** (2.86)	-34.83*** (6.77)
Income (in £100)	0.10*** (0.003)	10.49*** (0.14)	0.005*** (0.001)	0.0003*** (0.00002)	0.0006*** (0.00002)	0.002*** (0.0002)	0.13*** (0.007)	1.48*** (0.41)	0.02 (0.56)
R ²	0.78	0.72	0.55	0.60	0.32	0.65	0.60	0.37	0.14
Adj. R ²	0.69	0.75	0.56	0.53	0.41	0.56	0.51	0.03	0.07
Observations	720453	720453	720453	720453	720453	720453	720453	720453	720453
Accounts	38407	38407	38407	38407	38407	38407	38407	38407	38407

***, $p < 0.001$; **, $p < 0.01$; *, $p < 0.05$

Table 6.2: Fixed effects regression of the number of items, amount, standard deviation and skew, bounded by income, on the nine dependent variables, accounting for the fixed effects of account and the month of transaction.

6.3 Study 2: Online Experiment

The results from Study 1 are largely, but not fully, in line with prior empirical work and our predictions. Moreover, the results of this study are correlational, as such the causal relationship remains obscure. To further investigate we ran an online experiment in which participants were presented with 20 randomised numerical sequences of varying length, totals, standard deviation and skew.

In addition to our initial four hypotheses, we also wanted to see whether the transaction types (contactless, non-contactless), referred to as “condition”, made a difference. The condition as defined in this experiment is whether the participant is presented with a sequence which is exclusively made up of numbers derived from non-contactless transactions (non-contactless) or is presented with a sequence that is made up out of both non-contactless and contactless transactions (mixed). We hypothesized that the sequences which contain contactless transactions, those of the mixed condition, would stimulate underestimation. Our study has been pre-registered at <https://osf.io/3xvbs>.

6.3.1 Stimuli

The stimuli for this online experiment were derived from the transaction data used in Study 1. We were able to establish whether a transaction was contactless, or not. We then created two sets of data, one which was mixed, including both contactless and non-contactless transactions, and one set in which all contactless transactions had been removed, leaving only non-contactless transactions.

From the mixed data, the mixed condition was created, drawing transactions with a 50/50 distribution, where half of the transactions were contactless, and the other half were not. From the second data set we created the non-contactless condition, in which all transactions were non-contactless.

The transactions in both conditions were drawn into sequences of either 13 or 23. These two different lengths were the levels of our length variable, which we also varied. By crossing these two variables we have a 2 x 2 design.

In total, we created 80 numerical sequences, of which the first twenty consisted of twenty numerical sequences of 13 stimuli from the mixed condition, the second twenty consisted of twenty numerical sequences of 23 stimuli from the mixed condition, the third twenty consisted of twenty numerical sequences of 13 stimuli from the non-contactless condition and the final twenty consisted of twenty numerical sequences of 23 stimuli from the non-contactless condition.

Of the 80 numerical sequences, participants were only presented with 20 numerical sequences total. Five sequences were drawn from each “block”. The sequences within each block were drawn at random and then presented in random order. The four blocks were also presented in random order. All participants went through all conditions.

6.3.2 Sampling

The study was conducted via the Prolific Academic platform. As pre-registered, data collection stopped once a sample size of 500 was reached. The study took, on average, 17 minutes to complete.

6.3.3 Participants

A total of 512 individuals participated in the study. Six participants had to be excluded as they indicated having used an aid (e.g. notepad, calculator) during the study whilst it was explicitly stated that the task was to be completed without an aid, and one more participant had to be excluded due to answers that were incomplete, leaving a sample of 505 participants.

Participants were UK residents exclusively. We did not collect any further demographic data.

6.3.4 Procedure

The pre-registration of our procedure and analysis can be found on: <https://osf.io/3xvbs>. We recruited participants via Prolific Academic, who were directed to our online study in Qualtrics. Participants in this online study were presented with an overview of the study, indicating that they would be asked to sum up totals of the numerical sequences they would be presented with and that they would be presented with their results in the end. It was also explicitly stated that this was a difficult task. But that despite the difficulty, we encouraged them to estimate these totals to the best of their ability and strongly discouraged them from using an aid (e.g. calculator (app), note taking). After giving consent and their Academic Prolific ID, the participant was able to start the study.

Participants were then presented with the first of the 20 numerical sequences. Each sequence would only start displaying after the participant had pressed the “space bar” and then displayed the first number for 1000 ms, and then with a wait of another 1000 ms, displayed the next number. After all numbers in that particular sequence had been displayed, participants were asked to “Estimate the total of the numerical sequence you have just seen (up to 2 decimals, e.g. 0.12)”. After the participant had estimated the total

(forced response), they were presented with the next numerical sequence, which would not start until the participant pressed “space bar” again.

This process continued for 20 sequences. After the participant had estimated all 20 totals, they were asked to explain their strategy when trying to estimate these totals to the best of their ability. Next, participants were asked whether they did, or did not, use an aid. We encouraged participants’ honesty by indicating that the use of an aid would not have an effect on the compensation for their participation. Lastly, participants were presented with an overview of their estimates as compared to the true totals of the numerical sequences they had been presented with, and thanked for their time, before being taken out of the Qualtrics environment, back to the Prolific Academic platform.

6.3.5 Measures

From the study we can directly compare the answer (estimate) of the participant to the true total of the numerical sequence. To examine the five hypotheses we have come up with two dependent variables: error (estimate-total) and ratio (estimate/total). As pre-registered, our selection of variable was dependent on the distribution of the variable: if error was more normally distributed than ratio, we would use error as the dependent variable, and vice versa. From our results of the 505 participants who did not cheat and provided us with completed answers for all 20 sequences, we find that error is normally distributed to a much larger extent than ratio is. We use error as our dependent variable.

6.3.6 Analysis

Using the dependent variable of error (estimate – total), we apply a mixed model. First, as pre-registered, we excluded six participants who indicated having cheated (e.g. using a calculator or other aid in adding the stimuli), and excluded 1 more participant who did not complete all 20 trials, leaving us with 505 participants total. Second, we winsorized the bottom and top 5% of error, to minimize the effect of outliers. Third, error was modelled as a function of condition, controlling for length, with full random effects (including intercept, condition and length). For the random effects we followed the “keep it maximal” approach of dropping terms until the model converges (Barr et al., 2013). This was our primary analysis.

For our secondary analysis, we ran a similar model, where error was modelled as a function of condition, controlling for length, skew and standard deviation, with full random effects (including intercept, condition, length, skew and standard deviation). Again, for the random effects we followed the “keep it maximal” approach (Barr et al., 2013).

6.3.7 Results

When looking at our initial analysis, modelling error as a function of length and condition, we found a strong significant effect of length, as predicted; no significant effect of condition, as predicted; but also a large and significant interaction effect between length and condition, which moves in the opposite direction as predicted by the coefficients of the variables by themselves (see Appendix 6B: Table 6.6). The latter was not predicted and has not been corroborated by any literature. Additionally, adding in the standard deviation and skew, despite both being significant, increased rather than reduced the interaction effect. Looking at Tables 6.3 and 6.4, seeing the differences between the means and the medians, we find that this effect is entirely driven by the “Mixed 23” condition, with a mean error of -178, which is not in line with the mean errors for the three other conditions. Table 6.4 reveals that the median errors are much more similar, and that the extreme difference of condition “Mixed 23” has disappeared.

	Total	SD	Skew	Estimate	Error
Mixed, 13	593.89	101.31	2.46	584.68	-43.04 (-57.26, 38.84)
Mixed, 23	1025.98	114.16	3.07	834.98	-178.68 (-213.79, -168.23)
Non-Contactless, 13	772.95	112.35	2.14	733.21	-52.91 (-64.97, -14.51)
Non-Contactless, 23	1503.50	139.25	2.93	1628.09	-53.70 (-121.47, 368.64)
Number of observations	10100	10100	10100	10100	10100
Number of groups	505	505	505	505	505

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 6.3: The mean values of the independent and dependent variables for the four separate conditions. Numbers in parentheses are the 95% confidence intervals on the dependent variable, error.

	Total	SD	Skew	Estimate	Error
Mixed, 13	438.66	68.84	2.63	360	-8.91 (-56.96, 39.14)
Mixed, 23	882.41	94.51407	2.94	585	-39.24 (-62.02, -16.46)
Non-Contactless, 13	535.59	94.195	2.16	462	-13.61 (-38.84, 11.62)
Non-Contactless, 23	1578.44	108.77	3.08	1350	-37.30 (-282.35, 207.75)
Number of observations	10100	10100	10100	10100	10100
Number of groups	505	505	505	505	505

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 6.4: The median values of the independent and dependent variables for the four separate conditions. Numbers in parentheses are the 95% confidence intervals on the dependent variable, error.

Figure 6.1 (see Appendix 6A) plots the density curves of the four different conditions, and shows how this difference has occurred. Ranking the 80 sequences in terms of mean error (per sequence), we find that the three most extreme mean sequence errors are from the “Mixed 23” condition (sequences 33, 32, and 36) with mean sequence errors of -1020.25, -756.42, and -601.81, respectively. These errors are the values after having applied the 5% winsorisation. They differ largely from the other sequences, as the next mean sequence error is only -249.19, which is less than half of the prior mean sequence error. Looking at the other extreme, the positive mean sequence errors, we find that only eight sequences have positive mean errors. Of those eight sequences, four have a mean error under ten. The remaining four have errors above 300, the most extreme three being sequences 63, 61, 62, having errors of 581.26, 596.13, and 620.18 respectively.

Going through the data manually we do find that several participants have estimated the total values of the sequences by entering numbers which are indicative of them not paying attentions (e.g. numbers smaller than 100, or even numbers smaller than 1). We find that 21 participants have failed to adhere to the instructions of the experiment by giving estimates of that kind. However, even after excluding these participants, the means from the 6 most extreme conditions barely change, and the unexpected interaction effect of length and condition, driven entirely by these extreme values, persists. As such, we have made the decision to include all 505 participants, but to exclude the 6 most extreme sequences: excluding sequence 32, 33, 36 from the “Mixed 23” condition and sequence 61, 62, 63 from the “Non-Contactless 23” condition, leaving us with 505 participants and 9,343 observations.

Table 6.5 presents the results from our online experiment. Model 1 represents the primary analysis, in which error was modelled as a function of condition, controlling for length, with full random effects (including intercept, condition and length). Model 2 represents the secondary analysis, in which error was modelled as a function of condition, controlling for length, skew and standard deviation, with full random effects (including intercept, condition, length, skew and standard deviation). Having applied the “keep it maximal” approach, our models are linear mixed-effects models, with the intercept being the only random effect that withstood the approach as proposed by Barr et al. (2013). Models 3-5 were not pre-registered and are exploratory, their motivation and purpose are explained in the tertiary analysis.

Primary analysis

From our primary analysis (Model 1) we see that our intercept is significantly negative, showing that there is a tendency for underestimation in the default condition (mixed 13). The other coefficients are also negative, confirming the general tendency towards underestimation, as was expected.

Second, moving from a set length of 13 to 23, significantly increases underestimation, as shown by error becoming significantly more negative. This finding is in line with our hypothesis as we did expect error to be larger for longer set lengths. This is also in line with most research on memory, indicating that increased complexity, which can be induced by increasing the number of stimuli to be memorised, should decrease accuracy, and as a result increase error (Miller, 1956; Baddeley, 1994).

Third, looking at condition, we see that moving from the mixed to the non-contactless condition also increases underestimation, although its effect is not significant.

Lastly, looking at the interaction between length (23) and condition (non-contactless) we see the effect of underestimation becoming significantly stronger. Increasing both length and the proportion of non-contactless transactions in the stimuli moves error to be increasingly negative, showing a tendency for underestimation, as predicted.

Secondary analysis

Looking at Model 2, our secondary analysis, we see that results have slightly changed. First, the intercept remains significant, but only at the 0.01 level, and has become less negative, indicating a reduction in underestimation, for the default (mixed 13) condition. However, the general tendency for underestimating persists at a statistically significant level.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	−43.04*** (7.79)	−34.10** (10.93)	−36.68** (11.21)	−120.73*** (22.61)	14.55 (10.82)
Length: 23	−28.37*** (7.47)	−42.24*** (7.61)	−46.16*** (8.51)	−1.61 (13.93)	−17.57* (7.50)
Condition: Non-Contactless	−9.87 (7.15)	2.30 (7.18)	1.71 (7.20)	12.87 (7.56)	3.10 (7.20)
Length: Condition	−88.57*** (10.57)	−61.03*** (10.52)	−61.62*** (10.53)	−17.60 (12.16)	−10.83 (11.41)
Standard Deviation		−0.55*** (0.03)	−0.54*** (0.04)	−0.32*** (0.04)	
Skew		19.19*** (3.72)	21.76*** (4.48)	89.66*** (11.05)	−10.29*** (3.06)
Anchor			−8.84 (8.59)	−17.98* (8.66)	
Round Numbers				−0.82 (1.64)	
Under 10				−0.82 (1.49)	
Over 100				−25.52*** (2.65)	−32.23*** (2.03)
Kurtosis				−17.20*** (2.39)	
AIC	130896.38	130604.20	130599.00	130470.26	130615.45
BIC	130939.24	130661.34	130663.28	130563.12	130672.59
Log Likelihood	−65442.19	−65294.10	−65290.50	−65222.13	−65299.73
Num. obs.	9343	9343	9343	9343	9343
Num. groups: ID	505	505	505	505	505
Var: ID (Intercept)	17750.55	17968.43	17960.58	17858.89	17873.16
Var: Residual	64618.03	62478.39	62479.29	61658.92	62630.77

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 6.5: The effect of the independent variables or error, having excluded the 6 most extreme sequences, in terms of mean error. Model 1 shows the effect of length and condition on error. Model 2 adds to model 1 by including the effects of standard deviation and skew on error. Model 3 adds to model 2 by including the effect of the presence of an anchoring value. Model 4 adds to model 3 by accounting for any other possible factors. Model 5 removes all co-linear variables from model 4, to estimate the effect on error.

Second, the effect of set length, moving from 13 to 23, has become increasingly negative, showing an even stronger tendency for underestimation. The effect of condition, moving from mixed to non-contactless, has become positive, indicating overestimation, but remains insignificant. Looking at the interaction term, we again see a tendency for underestimation, which remains significant, but has decreased with the inclusion of standard deviation and skew in the model.

Third, looking at the newly introduced variables, standard deviation and skew, the results are as expected for standard deviation, but not for skew. We hypothesized that an increase in standard deviation would increase error, in the direction of underestimation. We find that the an increase of 1 in the standard deviation makes the estimate deviate -0.55 from the true total, showing underestimation, as predicted. We also hypothesized that an increase in skew would lead to higher error, also in the direction of underestimation. We find partial support for our hypothesis. An increase in skew does increase error as expected, deviating from the true total by 19.19, however, this term is positive, indicating that increases in skew (the distribution becomes more positively skewed, more frequently displaying numbers below the mean) lead to overestimation, rather than the predicted underestimation.

Tertiary analysis

After conducting our initial analysis as pre-registered, we are left with several results that require further exploring. Models 3-5 in Table 6.5 are our attempt at explaining the results from our primary and secondary analyses.

Model 3 is a copy of Model 2 with the addition of the anchor variable. In this analysis, anchor is a dummy variable indicating the presence of an anchor, defined as a the highest value in the numerical sequence being at least 50% of the total value of the sequence. We include this variable as we expect the presence of an anchor to make accurate estimation of the total easier, as half of the total value of a sequence is already captured within a single value, reducing the complexity of a sequence. However, we find that the effect of anchor is non-significant, yet including the variable does increase the coefficients of all the others, increasing error rather than reducing it.

Looking at Model 4, we have included all variables which could potentially have an effect on the accuracy of total estimation, in addition to those that were pre-registered. Still including the anchor variable, we now also account for the count of round numbers, the count of numbers under ten as well as the count of numbers over one hundred, in a numerical sequence. All of these variables can be used to reduce complexity: round numbers require less complicated calculations; numbers under ten can be rounded down

to zero, not being taken into account; numbers over one hundred can be used as anchoring points, where the focus is on the hundreds, and not on the tens or singles. All of these assumptions hold if the participants apply an addition and rounding strategy, which we will explore further in the next section. Last, we also included kurtosis as a measure having a potential effect of the perception of the total of a numerical distribution. Including all these variables, we find that the significant interaction effect between length and condition disappears. The term remains negative, as expected, but has lost significance. Condition has remained positive, yet non-significant, whereas the effect of length has disappeared completely, remaining negative but having turned insignificant. These changes can be explained by the other variables. The intercept remains negative and significant, but has increased by a large amount. The standard deviation remains negative and significant, yet has reduced slightly. Another large change has occurred in the skew variable, which has become increasingly positive and remains significant. The presence of an anchor has continued to impact underestimation positively, and has become significant at the 0.05 level. Both the inclusion of round numbers and numbers under ten have no significant effect on the error in estimating the distribution. Both the count of numbers over one hundred and kurtosis do have significant effects, contributing to the underestimation of the total of the distribution. Adding one additional number over 100 in a sequence increases underestimation by 25.52 and an increase of kurtosis by one level explains an additional increase of 17.20 in the underestimation of the total distribution.

Despite Model 4 providing us with a clearer idea of which variables impact (under)estimation, we do find that several of these variables are highly correlated. Starting with our primary analysis, we find that length is highly correlated with numbers under ten (.69) and round numbers (.57). For condition, we find no correlations over .44 (numbers over one hundred). Looking at standard deviation we find high correlations of .54 with skew, and .54 with numbers over one hundred. Looking at skew, we find additional high correlations with kurtosis (.95), anchor (.55) and the aforementioned standard deviation (.54). We decided to exclude all variables that have correlations above .5, starting with the variables from our primary and then secondary analysis. We decided to drop standard deviation rather than skew, as the latter has always had much larger effects, and holds more explanatory power. Having dropped standard deviation, numbers under ten, round numbers and kurtosis, we are left with Model 5. We now find that the intercept has become positive, but has also lost significance. The effect of length has become significant again, supporting the hypothesis that the longer a sequence is, the more complex it is and the bigger the error becomes, with a general tendency towards underestimation. Both condition and the interaction term remain insignificant. Skew remains significant, but has turned negative, in line with our hypothesis. The only variable that we did not

pre-register that does not have a correlation of above .5 is the count of numbers over one hundred in a numerical sequence. We find that its effect remains significant and negative, leading the presence of numbers over one hundred to underestimate the total of a distribution, which would fit with a rounding strategy.

Strategy

We have hinted at the use of a rounding strategy throughout this section. Of the 505 participants in our study we find that 76.9% indicated using an addition strategy, and that 61% indicated using rounding as a strategy as well. There is large overlap between these two pools of participants: 45.2% participants used simplified (through rounding) addition of the numbers in the sequences to estimate their total. Other strategies mentioned were guessing or guesstimating (20.8%) and a lack of strategy, where participants also felt that they were not doing very well (3.7%).

6.4 Discussion

6.4.1 Findings

We have conducted two studies to study the effect of the underlying spending distribution on expenditure recall and estimation. We hypothesized that increases in the number of transactions, total spending, standard deviation and skew would have detrimental effects on expenditure recall and estimation, and therefore negatively impact personal finance management.

In Study 1 we analysed data from a Financial Aggregator App to establish the effects of the number of transactions, total spending, standard deviation and skew on personal finance management. We find that increasing the number of transactions is associated with an increase in spending and all forms of short-term debt (a proxy for expenditure recall). Increasing the total amount of the distribution, the total monthly spend, is associated with an increase in the number of transactions, unsecured loan usage, credit card debt and the number of cash withdrawals, but negatively impacts the usage of overdraft, the latter being the opposite of our predictions. An increase in the standard deviation of the spending distribution is associated with significant decreases in the number of transactions, the likelihood of using unsecured loans, cash withdrawals and credit card debt, going against our predictions. Last, we find that increasing the skew of the spending distribution is associated with a significantly higher value and volume of spending, a significant increase in both forms of debt (overdraft and unsecured loans), as well as a significant decrease

in savings. The increase in overdraft and unsecured loan usage, as well as the decrease in savings are indicators of a reduced ability to manage one's finances. The results from Study 1 reject hypothesis 3 (standard deviation), but are in line with hypotheses 1, 2 and 4, showing that number of items, total spending and skew are associated with significantly detrimental effects on personal finance management and proxies of expenditure recall, whereas the standard deviation does not. The results are especially strong for the measure of skew. However, all these results are correlational and cannot be used to make causal claims.

In Study 2, we conducted an online experiment to establish a causal relationship between the error in estimating the total of a distribution and the four variables of interest. We hypothesized that increases in the number of transactions (1), total spending (2), standard deviation (3) and skew (4) would reduce the accuracy of expenditure estimation, favouring underestimation. We find support for our first hypothesis, showing that the length of a sequence, the number of items in a distribution, has a significant impact on the error in estimating the total of a distribution, favouring underestimation. Looking at hypothesis 2, we do not test for the effect of total in our models, as error is highly correlated with the total of the distribution ($r = -.34$). This correlation indicates that if the total of a distribution were to increase by 100, error would decrease by 34, again favouring underestimation. Looking at hypothesis 3, we find a minor effect of standard deviation, an increase in the standard deviation of the numerical sequence leading to increased underestimation, however this effect is minimal. Last, looking at hypothesis 4, the effect of skew on estimation accuracy is large and significant and predominantly positive, meaning that an increase in skew leads to an increase in error, as predicted. However, the error is favouring overestimation, rather than the underestimation that we predicted. As such, our findings are only partially in line with hypothesis 4. In our final model (Model 5), an increase in skew does predict increased underestimation, as well as the effect of length retaining its significance. The main variable explaining the error of estimation is the count of numbers above one hundred in a numerical sequence. The model continues to predict a general tendency towards underestimation, in line with findings by Brusovansky, Vanunu, and Usher (2019) and Scheibehenne (2019).

Contrary to Brusovansky, Vanunu, and Usher (2019) we find that most participants use an addition strategy when being presented with numerical sequences, rather than use an averaging approach. Additionally, we establish that there is a general tendency to underestimate, likely due to the rounding that is being done when adding up the numbers. The latter finding being in line with previous research (Brusovansky, Vanunu, and Usher, 2019; Scheibehenne, 2019).

Moreover, contrary to Scheibehenne (2019) we do find an effect of the underlying distribution. Despite the general tendency to underestimate, as established by proxies in Study 1 and the sign of error in Study 2, we do find that the number of stimuli (length) and the skew of the distribution have a significant effect on the accuracy of estimating the total of the distribution. Additionally, although correlated with skew, we also find an effect of kurtosis, the fifth moment, on the estimation accuracy. The strongest predictor of underestimation remains to be the count of numbers over one hundred, favouring an addition and rounding down strategy.

To return to our overarching theme, the direct effect of payment methods on payment distribution, and their indirect effect on personal finance management; both contactless (Chapter 4) and mobile payments (Chapter 5) have been linked to increased transactions, increased spending and increased overdraft fees, the latter indicating a reduced capability to accurately keep track of one's spending and remaining resources. These newer payment methods also favour more impulsive (read: smaller) expenses, the average contactless transaction being below £10, skewing the spending distribution. We have now also linked those changes in the spending distribution directly to worsened personal finance management, finding increased spending and reduced accuracy of spending recall, as measured in overdraft usage and short-term debt (Study 1) and increased underestimation of the total of a distribution (Study 2).

6.4.2 Limitations

The results obtained in Study 1 are, at best, correlational, due to the nature of the data provided by the Financial Aggregator App. To address this issue, we conducted Study 2, establishing a causal relation between the number of transactions, total spending, standard deviation, skew and the accuracy of estimation.

Another possible limitation may be the surprising finding of the interaction between condition and length in Study 2. Our conditions, despite being derived from different payment mechanisms, do not differ significantly in any characteristics. When accounting for all possible variables (Model 4), as well as excluding highly correlated variables (Model 5), this interaction disappears. We are confident that we have resolved this issue by making informed exclusions of both sequences and variables, and are confident that our fifth and final model represents the results accurately.

6.4.3 Contributions

In this chapter we establish a link between payment methods, spending distributions and personal finance management, measured in proxies of recall accuracy (Study 1) and accuracy of estimation (Study 2).

The initial assumption was that payment methods directly impacted personal finance management, by increasing spending (Feinberg, 1986; Hirschman, 1979; Prelec and Simester, 2001; Runnemark, Hedman, and Xiao, 2015; See-To and Ngai, 2019; Soman, 2003; Tokunaga, 1993), reducing the accuracy of expenditure recall (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; Srivastava and Raghubir, 2002), reducing impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and increasing debt accumulation (Gross and Souleles, 2002; Lee, Abdul-Rahman, and Kim, 2007). We show that these effects might not be as direct as expected, and show that the shifts those payment methods cause in the spending distribution (e.g. increasing the number of transactions, total spending, standard deviation and skew) also have an effect on proxies of recall accuracy and accuracy of estimation of the total of a distribution.

Second, we contribute to the few papers that have looked at the underlying characteristics of a distribution, and its effect on estimation. Our findings are only partially in line with those by Scheibehenne (2019) and Van Ittersum, Pennings, and Wansink (2010) who also find a tendency towards underestimation, but find that the underlying characteristics of the distribution do not matter. We, on the other hand, find that both skew and the number of items (transactions, stimuli) significantly impact both personal finance management (spending, debt, savings), as well as the accuracy of estimating the total of a spending distribution.

Last, we show these effects using both real world transaction data and an online study. This mixed methodology enables us to establish a causal link, as well as produce results with high external validity.

6.4.4 Further Research

Research regarding payment methods is slowly increasing and several theories have been proposed to explain why different payment methods lead to different behaviours (e.g. the pain of paying (Zellermayer, 1996), transparency (Soman, 2003), decoupling (Raghubir and Srivastava, 2008) and multi-functionality (Gafeeva, Hoelzl, and Roschk, 2018)). However, these theories assume a direct effect of payment method, often exclusively focusing on spending. Later research has extended these theories to also fit explanations of reduced expenditure recall accuracy (Gross and Souleles, 2002; Raghubir and Srivastava,

2008; Srivastava and Raghurir, 2002), reduced impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and debt accumulation (Gross and Souleles, 2002; Lee, Abdul-Rahman, and Kim, 2007). It is plausible, however, that the effect of payment method beyond spending is indirect, rather than direct. Further research is warranted to understand the mechanisms underlying the effect of payment method on spending distribution and the effect of spending distribution on personal finance management, measured in accurately keeping track of expenditures, as well as estimating the total of a set of expenditures. We have tried to do exactly that in this research, but further work is required to disentangle these possible direct and indirect effects.

In addition, research on the effect of the underlying characteristics of a distribution on the perception of said distribution remains scarce and contradictory. We did find an effect of several characteristics, length and skew, to be of significant impact on both personal finance management and estimation, whereas work by Scheibehenne (2019) and Van Ittersum, Pennings, and Wansink (2010) does not. Moreover, work by Tripp and Brown (2016) and Parducci (1965; 1968) has found there to be a preference for negatively skewed distributions, but poses no explanation as to why this preference occurs. Further research is required to understand why people have a preference for certain distributions, and whether this may be due to an error in estimating the total of the distribution or different aspects of the distribution itself.

Further research may also want to dig deeper to see whether the findings of prior research apply to all types of distributions. It may be possible that the underestimation found with grocery shopping (Scheibehenne, 2019; Van Ittersum, Pennings, and Wansink, 2010) only applies to grocery shopping, and may not apply to wage distributions (Parducci, 1965; 1968; Tripp and Brown, 2016). Although there is strong evidence to belief that underestimation is a result of poor mental arithmetic and innate to human complex reasoning (Thaler, 1999), our findings in Study 2 do not always support the underestimation account. Further research is required to establish exactly when people underestimate, which characteristics influence underestimation and how this can be counteracted.

Appendix 6.A The Density of Error Per Condition and Length.

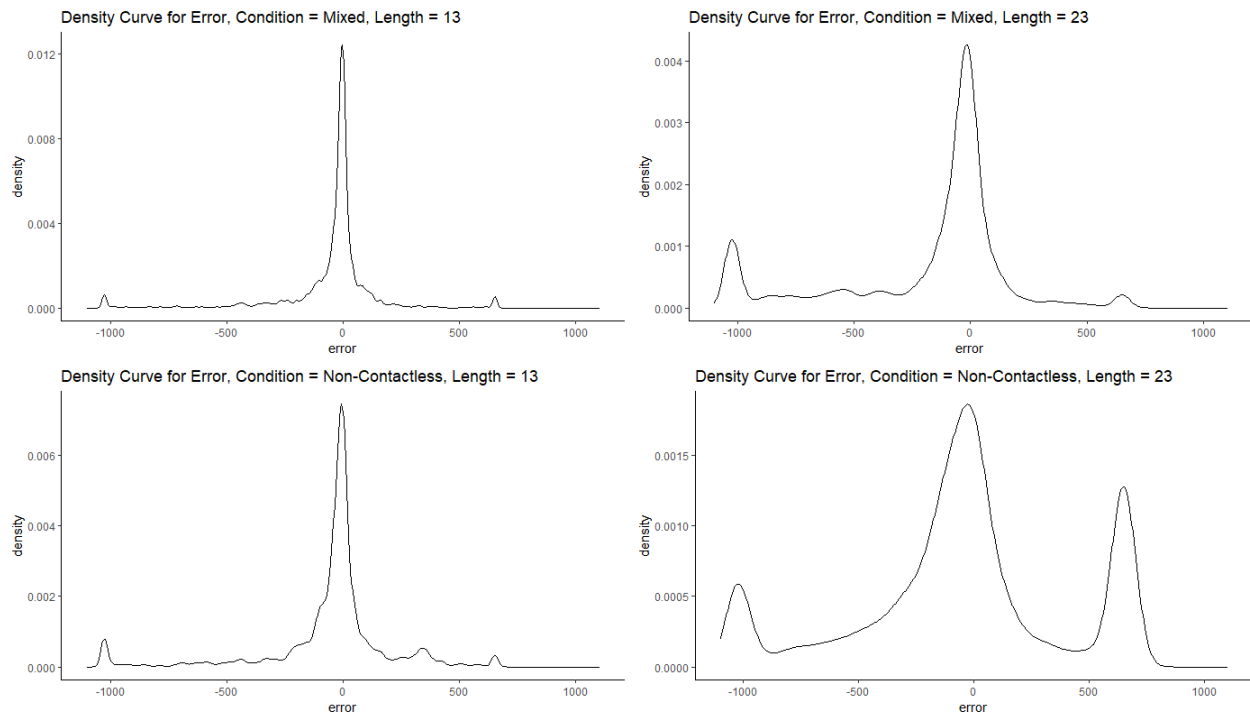


Figure 6.1: The Density of Error Per Condition and Length.

Appendix 6.B The Effect of the Independent Variables on Error, Without Exclusions.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	−43.04*** (8.45)	−27.43* (11.92)	−4.87 (12.00)	84.89*** (18.37)	76.84*** (12.20)
Length: 23	−135.64*** (8.88)	−148.22*** (8.55)	−98.19*** (9.42)	−188.34*** (14.39)	−105.48*** (8.89)
Condition: Non-Contactless	−9.87 (8.88)	20.29* (8.38)	28.03*** (8.34)	22.19* (8.63)	8.21 (8.78)
Length: Condition	134.85*** (12.56)	145.02*** (11.67)	141.31*** (11.59)	124.33*** (13.35)	245.36*** (13.02)
Standard Deviation		−1.34*** (0.04)	−1.45*** (0.04)	−1.30*** (0.04)	
Skew		48.76*** (4.10)	20.80*** (4.66)	−53.66*** (6.12)	−27.18*** (3.60)
Anchor			105.02*** (8.56)	30.02** (9.36)	
Round Numbers				2.17 (1.80)	
Under 10				3.22* (1.56)	
Over 100				−0.91 (2.71)	−52.98*** (2.33)
Kurtosis				23.79*** (1.30)	
AIC	145614.79	144184.38	144031.02	143688.61	145010.90
BIC	145658.11	144242.14	144096.01	143782.48	145068.66
Log Likelihood	−72801.39	−72084.19	−72006.51	−71831.31	−72497.45
Num. obs.	10100	10100	10100	10100	10100
Num. groups: ID	505	505	505	505	505
Var: ID (Intercept)	16124.82	16828.91	16886.20	16990.19	16380.31
Var: Residual	99583.61	85761.83	84448.28	81560.61	93575.55

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 6.6: The Effect of the Independent Variables on Error, Without any Exclusions.

Appendix 6.C The Effect of the Independent Variables on Error, Models Capped at 500

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	−43.04*** (7.79)	−34.10** (10.93)	−36.68** (11.21)	−120.73*** (22.61)	14.55 (10.82)
Length: 23	−28.37*** (7.47)	−42.24*** (7.61)	−46.16*** (8.51)	−1.61 (13.93)	−17.57* (7.50)
Condition: Non-Contactless	−9.87 (7.15)	2.30 (7.18)	1.71 (7.20)	12.87 (7.56)	3.10 (7.20)
Length: Condition	−88.57*** (10.57)	−61.03*** (10.52)	−61.62*** (10.53)	−17.60 (12.16)	−10.83 (11.41)
Standard Deviation		−0.55*** (0.03)	−0.54*** (0.04)	−0.32*** (0.04)	
Skew		19.19*** (3.72)	21.76*** (4.48)	89.66*** (11.05)	−10.29*** (3.06)
Anchor			−8.84 (8.59)	−17.98* (8.66)	
Round Numbers				−0.82 (1.64)	
Under 10				−0.82 (1.49)	
Over 100				−25.52*** (2.65)	−32.23*** (2.03)
Kurtosis				−17.20*** (2.39)	
Num. obs.	9343	9343	9343	9343	9343
Num. groups: ID	505	505	505	505	505
Var: ID (Intercept)	17750.55	17968.43	17960.58	17858.89	17872.83
Var: Residual	64618.03	62478.39	62479.29	61658.92	61679.55

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 6.7: The effect of the independent variables or error. Models are run on data that has the mean error capped at 500 (and -500), without the express exclusion of participants or numerical sequences.

Chapter 7

Discussion

7.1 Findings Summarised

This dissertation aims to contribute to the literature on payment methods, and to extend the already existing theories to capture newer payment methods and their effects on several behavioural outcomes.

In Chapter 3 we examined the effect of contactless payments on expenditure recall, a behavioural outcome associated with personal finance management (Gross and Souleles, 2002) and also linked to spending (See-To and Ngai, 2019). Prior work showed that contactless payment methods were associated with increases in spending (James, 2017; MasterCard US, 2011; Trütsch, 2014; See-To and Ngai, 2019), reduced spending awareness (See-To and Ngai, 2019) and feelings of reduced control of one's finances (James, 2017). Theories on payment methods extended to fit contactless payment methods explain these effects by contactless payment methods being less physical and quicker than cash, and as a result less salient (Soman, 2003; Zellermayer, 1996). We examined the effect of contactless on expenditure recall by conducting two studies. Study 1 was an observational study, conducted in an on-campus grocery store, approaching customers immediately after they had done their shopping, asking them to recall their spending. Our findings showed that contactless payments methods were associated with reduced accuracy of recall as compared to cash, a finding in line with the pain of paying (Zellermayer, 1996). However, contactless methods were associated with a higher accuracy of expenditure recall compared to PIN-verified cards. This difference was predominantly driven by customers who used credit cards (both contactless and PIN-verified). The contrasts between PIN-verification and contactless cards debit, as well as debit and credit cards combined, did encompass zero, meaning that the true difference might be zero. Despite

having established an effect of payment method, the main driver of expenditure recall was the number of items purchased. Customers who bought only one item were 32% more likely to be accurate in estimating their expenditure than those who bought more than one item. These findings are in line with the short-term memory account proposed by Magnussen et al. (1991) who argue that exposure to prices and duration of the transaction are important factors in being able to recall expenditures correctly. Overall, Study 1 shows that contactless payments are associated with significantly worse expenditure recall as compared to cash.

To establish a causal effect of contactless, explaining the possible difference from PIN-verified methods and finding the underlying mechanism driving the worsened recall, we conducted Study 2. Participants were recruited through Prolific Academic and randomly assigned into one of three payment conditions: cash, contactless debit card or PIN-verified debit card. A number of additional measures were accounted for: income, being on a budget, monthly grocery spending, the spendthrift-tightwad scale (STS), as well as the pain of paying experienced during the grocery shop. We conducted two analyses: the first focusing on expenditure recall and the second focusing on the pain of paying. Our first analysis revealed that expenditure recall was significantly worse with contactless payment methods as compared to cash, replicating the finding in Study 1. Expenditure recall with PIN-verified debit cards was not found to be significantly different from cash. We also continue to find significant effects of the number of items purchased, as well as the STS, indicating that personal characteristics do matter in the accuracy of expenditure recall. Tightwads, people who do not enjoy spending money, achieve higher levels of accuracy when recalling their expenditure. Our second analysis looks into the mechanism driving the worsened expenditure recall associated with contactless payments. We find no support for the pain of paying as the driving mechanism. In our first analysis the pain of paying does not impact accuracy of recall, whereas it was hypothesized that more painful spends would make for more salient spends, in turn improving expenditure recall. In the second analysis we do not find an effect of payment method on the pain of paying. There are no significant differences in the pain of paying between the three methods of payment. The main drivers of the pain of paying were whether the customer was on a budget (salience), and which point of sale was being used. The latter showed a significant decrease in the pain of paying when using the much quicker self-service check-out. To further explore the possible relationship between the pain of paying, payment method and expenditure recall we conducted mediation test of which the result was found to be insignificant. We continued to find a 1-item effect, with participants who purchased only one product now being 29% more likely to recall their spending accurately, compared to those who bought multiple items.

Our results strongly indicate that correct expenditure recall is not driven by mechanisms such as the pain of paying. Expenditure recall mainly seems to be driven by the memory account, showing that contactless payments, with their reduced exposure and increased quickness of the transaction, are associated with significantly reduced accuracy of expenditure recall (Magnussen et al., 1991). The pain of paying can be predicted by almost all of our covariates, yet the majority of those do not significantly impact expenditure recall. The relationship between expenditure recall, both in short-term and longer-term memory, as well as its relation to the pain of paying clearly warrants further research.

In Chapter 4 we studied the effect of contactless payment methods on several measures of personal finance management: spending (value and frequency), overdraft fee occurrence (as a proxy of expenditure recall), unsecured loan usage, cash usage, savings and credit card debt.

In line with theories such as the pain of paying, we expected contactless payments to stimulate spending, in both value and frequency, in line with research on credit cards (Feinberg, 1986; Gross and Souleles, 2002; Hirschman, 1979; Prelec and Simester, 2001; Prelec and Loewenstein, 1998; See-To and Ngai, 2019; Soman, 2001; Thomas, Desai, and Seenivasan, 2011; Tokunaga, 1993). We also expected to see an increase in overdraft fees, as a proxy for accurate expenditure recall and the ability to correctly keep track of money spent and money left, also known as mental accounting (Thaler, 1999). This hypothesis was fuelled by findings from Chapter 3, showing that contactless payment methods do significantly reduce the accuracy of single expenditure recall. We also hypothesized that as a result of diminished personal finance management, people would save less due to increases in spending, and potentially even hold more credit card debt to support their increased spending. Lastly, we expected the onset of contactless usage to reduce cash usage, as contactless methods were deployed as a cash replacement, making paying faster, safer and more convenient (Krol et al., 2016).

We used a transaction data set from a Financial Aggregator App and were able to identify the onset of contactless usage to the day and identify this as “point zero”. From this point onward, a *before* and an *after* were created. These before and after periods are measured in 12 months each; 12 months before the first month contactless was used, and 12 months after the first month contactless was used. Our timeline spans a total of 25 months. In those 25 months, we exclusively looked at individuals who held one contactless card (the contactless account), as well as accounts on which contactless payment methods were never enabled (the non-contactless accounts). We ran eleven fixed effect regressions, the fixed effects being the individual user and the calendar month. Looking

at the contactless accounts we find that the onset of contactless usage is associated with significantly increased spending frequency and value, as well as significantly increased cash withdrawals and savings. Contactless usage was not associated with increased overdraft fees, unsecured loans, or credit card debt, indicators of reduced personal finance management. We also find that the onset of contactless usage is associated with significant increases in the money credited into the contactless enabled accounts, as well as internal transfers made to the account. Running the same regressions for the non-contactless accounts we do not see any significant decreases in any of the dependent variables. Looking at the overall user level, our results show that the onset of contactless usage continues to be associated with a significant increase in spending frequency and value, as well as significantly increasing savings and cash usage. No effect on overdraft, unsecured loans or credit card debt was found. Although more money is being spent, we find no indicators of people losing control of their personal finances, as proposed by (James, 2017). On the user level we also continue to see a significant increase in credits and internal transfers made associated with the onset of contactless. This result indicates that the user is moving around more money, towards the contactless account, as it has become easier and more convenient to use as the main spending account (Krol et al., 2016). This increase in credits is able to explain the shift in account usage pattern, favouring the contactless account. Looking at the contactless account, the internal transfers explain approximately 59% of the increase in money being used, looking at spending and saving combined. Looking at the contactless user, the internal transfers explain approximately 70% of the increase in money being used, leaving 30% of the increase in money used to be explained by the onset of contactless usage.

In Chapter 5 we aimed to replicate the findings associated with contactless in Chapter 4 for a newer payment method: mobile payments. We applied the same methodology, conducting eleven fixed effect regressions, fixing the effects of user and calendar month.

Mobile payments are both novel in terms of their introduction to the payment landscape as well as their position on the spectrum of payment methods. For the first time the functions of paying and keeping track of those payments have been unified in a single device, making the device multi-functional (Gafeeva, Hoelzl, and Roschk, 2018). This multi-functionality has been used to argue that mobile payments should be less salient, as payments are not the only function of the device. Reduced salience is often referenced as the reason to why payments would be less painful (Zellermayer, 1996) and less transparent (Soman, 2003). The reduced salience is predominantly driven by the simplicity of the payment, as such we call this the simplicity account. However, theories on mental accounting (Thaler, 1999) do not support this argument, as the mobile device is also linked to online

banking apps, as well as the Financial Aggregator App from which the data was obtained. Through the use of these apps, mental accounting is supported by the ability of actual accounting - keeping track of expenditures, and the money which remains, in real time, via the mobile device. Due to increased exposure to their spending, consumers should become increasingly aware of both their spending and their financial situation (Magnussen et al., 1991; Huebner, Fleisch, and Ilic, 2020). Therefore, transactions via a mobile device should become more salient. We call this the salience account. We are dealing with two competing theories: one of simplicity and one of salience. The theories compete in terms of hypotheses: the simplicity accounts predicts increased spending, in both value and frequency, increased overdraft fees due to a decreased awareness of spending, increased credit card debt usage to support the increase in spending, and a decrease in both cash usage and savings. The salience account predicts the opposite trend: decreased spending, in value and frequency, decreased overdraft fees due to increased spending awareness, reduced credit card debt, increased savings and potentially increased cash usage, as cash is often heralded as a budgeting tool (Doyle et al., 2017).

Our methodology is a direct replication of that in Chapter 4. We use the data from the Financial Aggregator app, identify the very day on which mobile payments were first used at the point of sale, and identify this as “point zero”. From this point onward, a *before* and an *after* were created. These before and after periods are measured in six months each; six months before the first month mobile payments were used, and six months after the first month mobile payments were used. Our timeline spans a total of 13 months. In those 13 months, we exclusively looked at individuals who held one mobile enabled account, as well as accounts on which mobile payment methods were never enabled (the non-mobile accounts). We ran eleven fixed effect regressions, the fixed effects being the individual user and the calendar month. Looking at the mobile enabled accounts first, we find that mobile payments are associated with significant increases in spending, both frequency and volume, supporting the simplicity account. At the same time we find that mobile payments are associated with a significantly reduced likelihood of incurring overdraft fees, as well as a significant increase in cash usage and savings, with no effect on credit card debt usage or unsecured loan usage. The results support the salience account, when looking at the mobile enabled accounts. The results of the same analysis on the non-mobile enabled accounts shows a significant decrease in the frequency of spending, but no other significant changes indicative of there being a compensatory mechanism. On the overall user level, we find that the onset of mobile payments is associated with a significant increase in the frequency of spending, as well as a significant increase in cash usage and savings. The former supports the simplicity account, the latter two support the salience account. The lack of significantly increased spending (in value), overdraft

occurrence and credit card debt usage does seem to indicate that the simplicity account is not enough to stimulate spending to a large extent. It is possible that this effect did occur, but was mediated in the opposite direction by the salience account. However, this is mere postulation. Unlike Chapter 3, we find no indication of significantly increased credits or internal transfers into the mobile enabled account. The compensation mechanism is derived entirely from the non-mobile account, which does display reduced activity associated with the onset of mobile payment usage on the other account. This shift in activity partially explains the increases in transactions, cash usage and savings associated with mobile payments.

In the previous three chapters we have assumed, supported by prior literature, that the method of payment has a *direct* effect on behavioural outcomes, such as spending and expenditure recall. However, in this chapter we explore whether this relationship may be more *indirect* by changing the spending distribution, and this change being responsible for the effects we found in Chapters 3-5.

Prior work on numerical distributions does indicate there to be an effect of total (Scheibehenne, 2019; Van Ittersum, Pennings, and Wansink, 2010; Hutchinson, Wilke, and Todd, 2008), frequency (Snyder, Blank, and Marsolek, 2008; Thomas, Desai, and Seenivasan, 2011), standard deviation (Thomas, Desai, and Seenivasan, 2011; Brusovansky, Vanunu, and Usher, 2019), skew (Parducci, 1965; Parducci, 1968; Parducci, Thaler, and Anderson, 1968), and kurtosis (Scheibehenne, 2019) on the estimation of the total of a distribution. Additionally, research also found there to be a strong preference for negatively skewed distribution, indicating that those are often overestimated (Parducci, 1965; Parducci, 1968; Parducci, Thaler, and Anderson, 1968).

In the previous chapters we have found that the onset of both contactless and mobile payments changes the spending distribution: both the frequency (number of transactions) and the total (monthly spending) increase. Additionally, research by Thomas, Desai, and Seenivasan (2011) has shown a relationship between payment methods and spontaneous, smaller impulse purchases. As these purchases are of lower value, they skew the spending distribution towards becoming more positively skewed and increase the standard deviation. We hypothesize that all four measures, frequency, total, standard deviation and skew, are associated with a change in personal finance management, especially the ability to accurately track expenditures. We expect this change to be for the worse. Meaning that an increase in frequency, total, standard deviation or skew will lead to a decrease in the ability to correctly track expenditures, and manage personal finances.

To test our hypotheses we conducted two studies. Study 1 is an analysis of the same Financial Aggregator App data as used in Chapters 4 and 5. Looking at a sample of

38,407 accounts, we run nine fixed effect regressions, fixing effects for the account and the calendar month. Our nine dependent variables are the same as before (spending, overdraft, unsecured loans, cash usage, credit card debt, savings), excluding credits and internal transfers. The results show that increasing the number of transactions is associated with a significant increase in spending, overdraft occurrence and savings. The latter result, however, is marginal. Increasing the total of the distribution is associated with a significant increase in the number of transactions and the number of cash transactions, as well as a significant reduced repayment of credit card debt. However, it is also associated with a significant decrease in overdraft fees, and a small but significant increase in savings. Increasing the standard deviation of the spending distribution is associated with less transactions, reduced credit card debt and increased savings, contradicting our initial predictions. Increasing the skew of the spending distribution is associated with the largest effect sizes: an increase in skew is associated with significant increases in the number of transactions, spending, overdraft, credit card debt, and a significant decrease in savings. Study 1 shows a strong effect of the number of transactions and an even stronger effect of skew on personal finance management.

In Study 2 we conducted an experiment on expenditure estimation to corroborate the findings in Study 1, and to provide a causal explanation. Participants were presented with 20 randomly selected numerical sequences with different totals, frequencies (13 or 23), standard deviations and skews. The values of the numerical sequences were once more derived from the transaction data provided by the Financial Aggregator App. One half was derived from a data set which had both contactless and non-contactless transactions (the “mixed” condition), the other half was derived from a data set with exclusively non-contactless transactions (the “non-contactless” condition). Block 1 had a total of 20 numerical sequences of length 13 of the “mixed” condition. Block 2 had a total of 20 numerical sequences of length 23 of the “mixed” condition. Blocks 3 and 4 replicate this pattern, but for the “non-contactless” condition. In total, there were 80 numerical sequences, of the four different blocks we had created. Of these 80 numerical sequences participants saw 5 randomly assigned numerical sequences of each block. The blocks were also randomised. After having been presented with a numerical sequence, participants were asked to, to the best of their ability, estimate the total of the numerical sequence they had just seen. Our results show, looking at five separate models, that the variables having the biggest effect sizes are frequency (sequence length) and skew. Accounting for different variables such as rounding, anchoring, small numbers, large numbers and kurtosis in our models, we continue to find a significant impact of length and skew, as well as a large and significant effect of numbers over one hundred. The coefficient is negative, indicating rounding down when these numbers are present. The likely explanation for this is a

combination of anchoring and rounding. Throughout all models, the coefficients of length and skew have remained significant.

In this chapter we have conducted two studies: one with high external validity showing a large effect of the number of transactions and skew of the spending distribution on personal finance management, and the second corroborating these findings and allowing us to make causal claims. Newer methods of payment, contactless and mobile, have been associated with spending more and more frequently, favouring smaller impulse spends, skewing the spending distribution. This relationship and possible mediation effects do warrant further research.

7.2 Limitations

Both of the studies conducted in Chapter 3 show an effect of contactless payments on expenditure recall, showing that expenditure recall using contactless payment methods is significantly worse than expenditure recall when using cash. However, both studies do suffer some limitations. Study 1 was observational in nature, as participants were approached after they had gone shopping with their payment of choice. Our results do not account for individual differences, such as preference for a certain payment method. It is also difficult to draw generalisations from the sample of Study 1: within the store and times sampled, customers, on average, only bought 3 items, and had a modest expenditure of £3.28. It is possible that different effects and effect sizes would have been found testing in stores with higher single purchase values and larger basket sizes, as seen with research done by See-To and Ngai (2019) and Thomas, Desai, and Seenivasan (2011). Moreover, different effects could be found when testing for longer periods of time, as seen with research done by (Srivastava and Raghubir, 2002). We also did not account for financial context: the amount of attention that is paid to spending is often dependent on the consumer's financial situation. In Study 1 we exclusively looked at the effect of payment method, not accounting for other financial aspects influencing the transaction. Study 1 exclusively aimed at establishing an effect of contactless on expenditure recall, a proof of concept, but did not account for the mechanism driving the effect. Our results show that we did find an effect, but given that this effect is not the effect that was expected, the mechanism underlying the effect, which was assumed to be the pain of paying, warrants further exploration. Study 2 was conducted to address these limitations. Despite continuing to find an effect of contactless, Study 2 has some limitations as well. The main difference between Study 1 and Study 2, aside from the additional factors accounted for, is the time differential. In Study 1 participants were approached immediately after

their shopping. The expenditure recall being that of short-term memory. In Study 2, participants filled in the survey and recalled the expenditures hours after the fact. This means we are testing for retrieval from longer-term memory. This difference indicates that it might be difficult to draw direct comparisons between Study 1 and 2 with regards to expenditure recall. It may also explain why there is no longer an effect of payment method on the pain of paying, which prior literature indicates we should find, as there are more salient factors at play when retrieving an expenditure from longer-term memory, such as stable personality traits (STS) and financial traits (being on a budget) rather than the fleeting effect of payment method. Further research should continue to address the impact of payment methods on memory, both short-term and longer-term memory for a variety of basket sizes and expenditures. Our studies show that contactless impacts both short-term memory for smaller basket sizes and longer-term memory for larger basket sizes, to the detriment of the consumer, as accuracy of recall significantly decreases.

In Chapter 4 we extend the findings of Chapter 3 by estimating the effect of contactless on a variety of factors implicated in personal finance management. We continue to find an effect of contactless, significantly increasing the number of transactions, monthly spending as well as savings. The limitations in Chapter 4 are mainly due to its sample: it is possible that those who install and use a Financial Aggregator App on their phone are potentially a non-representative sample in the population. It can be argued that they are either very financially interested and knowledgeable, using the app to their advantage, whereas it is equally possible that this is a sample that is financially impaired and is trying to make sense of their finances by using this app. A combination of these two assumptions is also possible, potentially cancelling each other out when looking at all of the data in aggregate. Moreover, we found the average user within our sample to hold quite a larger number of accounts. We only analysed those with five current accounts or less, excluding 10% of our initial sample. This also leads us to believe that part of the original user base is non-representative, in that they hold more accounts than the average person would, if they were only tracking their own finances, rather than those of others, or with regards to business enterprises. An additional concern is that there is a category of untagged spending within the data. We have no information on these transactions, as such it is difficult to see what their increased spending means for the personal financial situation of the user. However, this spending category is only associated with a non-significant increase of £6.74, explaining approximately 11% of the increase in spending. Additionally, the data strongly makes us suspect that untagged spending is not spending at all, but the transfers of money between accounts of the same user. Similarly, the increased account activity associated with the contactless account is taken away from other accounts, not registered with the app, and as such invisible to us. We do not have the full picture of the

users' financial situation in this specific data set, although we believe that our analysis has near fully negated this limitation.

Chapter 5 looks into the effect of mobile payments on personal finance management, showing support for the salience account as our results indicate a significant increase in transactions, but no (significant) increases in spending, overdraft, credit card debt and a significant increase in both cash usage and savings associated with the onset of mobile payment usage. However, Chapter 5 has similar limitations to Chapter 4, as it is based on the same data. We raise the same concerns based on the type of sample, the untagged transactions and the incomplete picture of the users' financial situations. It does have to be mentioned that the value of untagged spending, or as we suspect, internal transfers, is larger for the sample of mobile users in Chapter 5 than it is for contactless users in Chapter 4.

Last, Chapter 6 argues that the effect of payment method on personal finance management may be indirect rather than direct, and that the effects associated with payment methods (overspending, underestimating prior expenses) are better explained by changes in the spending distribution. We have conducted two studies to test this hypothesis. The results obtained in Study 1 are correlational, due to the nature of the data. These data are a random 10% sample of those also used in Chapters 4 and 5, and suffer the same limitations. However, research has long established there to be an effect of recall accuracy with regards to payment methods (Gross and Souleles, 2002; See-To and Ngai, 2019; Srivastava and Raghurir, 2002; Raghurir and Srivastava, 2008) and willingness to continue spending (See-To and Ngai, 2019; Runnemark, Hedman, and Xiao, 2015; Raghurir and Srivastava, 2009; Thomas, Desai, and Seenivasan, 2011). As such, we are comfortable extending our results to include effects on this particular data set. To complement Study 1 we conducted Study 2, conducting an online experiment presenting participants with 20 randomised numerical sequences varying length, total, standard deviation, skew and condition. We established a causal relation between those variables and the accuracy of total estimation, often measured as underestimation. We find a main effect of length and skew. Additionally, we find there to be an interaction effect between condition and length, where longer sequences derived from non-contactless transactions significantly reduce the accuracy of the total estimate. After further exploration we find that the "mixed" condition has lower totals, as there is a cap of spending on contactless transactions. We postulate that this is the main driver of our unexpected result. We have solved this limitation by going beyond our pre-registered analysis, conducting more exploratory analyses and are confident that our final model represents the results accurately.

Having addressed the limitations per chapter, we also want to address the limitations

of this dissertation specifically. Some of our chapters are grounded exclusively in data provided by a third party, here, a Financial Aggregator App. This pertains to Chapters 4 and 5, which, despite their robust results that have been approached from a multitude of angles, do not allow for causal inference. We find that both contactless and mobile methods of payment are associated with increased spending, both in value and frequency, as well as increased savings. However, we cannot argue that these are *caused* by the onset of contactless or mobile payment usage. Chapter 6, in which we look into the possible effects of the spending distribution on personal finance management, suffers similar issues: again we make use of the Financial Aggregator App data, making it impossible to draw causal inference for our findings that increased length (number of transactions) and skew are associated with worsened personal finance management. To address this limitation we conducted an experiment presenting participants with twenty numerical sequences, selected randomly from a total of eighty sequences, varying in set length, total, standard deviation, skew and condition, and continue to find a main effect of skew and set length (Study 2). The mixed methodologies within this dissertation helped address issues of causal inference.

Another concern of this dissertation specific to the third party data, as provided by the Financial Aggregator App is the ever present increase in savings. Savings here is defined at the difference between the money going out of the account (debit) for the purpose of savings, minus the money coming into the account (credit) having been flagged as coming from a savings account. The increase in savings associated with both contactless and mobile payments is not in line with theories such as the pain of paying, or the simplicity account in general. We have come up with three explanations, in addition to the salience account in Chapter 5, for this finding. First, it is possible that the account observed, as well as the user as a whole, increase their savings as a result of using the Financial Aggregator App. These apps are designed to make users increasingly aware of their spending and adjust their spending if they so desire. It is possible that those who installed a Financial Aggregator App did so to curb their spending and increase their savings. This explanation has two issues: this would not account for the increase associated with the onset of a specific payment method, nor would it explain the continued increase in spending associated with the onset of specific payment methods. Our second explanation focuses on account shifts. The accounts that have either contactless or mobile payment enabled on them become increasingly used, at the expense of other spending accounts of the user. It is possible that the increase in savings found is explained by these accounts becoming the dominant account of the user and now the main source of money being transferred into the savings account. This would have to be accompanied by reduced savings on the

other accounts of the user, some of which we do not have access to. In Chapter 5, looking at mobile payments, we do seem to find a decrease in savings, albeit not significant, on the non-mobile accounts. This is the main explanation we use in Chapters 4 and 5. Third, it is possible that there are issues with the flagging systems in place. From the perspective of the account the flagging of savings being debited (moving from the account being observed into a savings account not being observed) is flagged as savings in the Financial Aggregator App itself. However, money being credited into the account from a savings account had not been flagged by the app itself, but was flagged by us. It is possible that we have not sufficiently flagged the money moving into the account, and as such are underestimating the amount of savings being moved into the account, leading to a much larger savings differential than is true. Given the limited information on internal transfers and the lack of information on money being taken from non-registered accounts, we have tried our best to address this limitation within this dissertation, but we continue to be wary of interpreting these results.

In addition to the chapter and dissertation specific limitations, there are limitations within the field of study that need addressing. Starting with the concept of the pain of paying. Throughout this dissertation, the pain of paying was assumed to be a main driver of the effects associated with different payment methods. However, in line with prior work (Banker et al., 2017), we do not find an association between the pain of paying and accuracy of expenditure recall. In Chapter 3, we find no significant impact of pain of paying on expenditure recall, nor do we find a mediation effect between recall, payment method and the pain of paying. Looking at the pain of paying as a dependent variable, we find that it is largely predicted by whether the participant is on a budget, supporting the account by Magnussen et al. (1991), as those on a budget pay more attention to expenditures. Additionally, we are wary of the range indicated by the pain of paying: most participants indicated having experienced a pain of paying around 1 (using the -5, +5 scale), which indicates a slight pleasure of paying close to the point of neutrality ("0"). Most studies find negative values, not positive values (Knutson et al., 2007; Mazar et al., 2016; Rick, Cryder, and Loewenstein, 2008; Zellermayer, 1996).

More severe than our own studies not replicating the pain of paying is the idea that the pain of paying may not exist to the extent that we have assumed it to exist. Or for it to not exist at all. Prior work measuring the pain of paying has predominantly made use of self-reports. Participants were asked to rate their pain of paying, often on a -5 to +5 scale or on a 1 to 10 scale. There is a large literature questioning the validity of self-reported measures within the behavioural sciences (Brenner, Billy, and Grady, 2003; Hansen, Larsen, and Gundersen, 2021; Midanik, 1982; Morisky, Green, and Levine, 1986;

Pérez et al., 2015). See Rosenman, Tennekoon, and Hill (2011) for an overview of bias in self-reported data. In addition to the questionable validity of some types of self-reported data, the pain of paying is known to be offset by the reward experienced by the purchase of a good/service. Participants are asked to rate their pain of paying often immediately after the transaction (payment) when they know that they are about to obtain their purchase. It is conceivable that participants are unable to disentangle the pain of paying from the reward of their purchase and as such are rating a mixture of the two, rather than identifying the singular effect of the negative emotions associated with paying itself. This would explain the largely positive (pleasurable) experiences found in Chapter 3.

In addition to the studies using self-reported values of the pain of paying, some of the studies that observe the pain of paying behaviourally are grounded in expenditure priming (Mazar et al., 2016; Plassmann, Mazar, and Rangel, 2011; Prelec and Simester, 2001) as a way of increasing the pain of paying. Priming as a method has received a large amount of scrutiny as a lot of priming studies fail to replicate (Locke, 2015). Others have asked whether it is truly the *pain* of paying, rather than other negative emotions associated with paying at play (Santana, 2012). It is also possible that there is the effect of increased focus at play (Magnussen et al., 1991). The reiteration of prior expenses can also function as a boost in mental accounting, during which the participant realises how tight their budget is, increasing their focus on money dwindling and reducing their willingness-to-pay for further expenses. This would increase the *salience* of the next spend, but need not increase the pain of paying, if it were to exist. If this is the case the studies on priming pain of paying are priming attention and budget conscientiousness, not the pain of paying, and these results have been misinterpreted.

The pain of paying became increasingly accepted as a mechanism explaining differences in purchasing decisions as neuroscience studies, predominantly using fMRI techniques, showed activity in the insular cortex (associated with the experience of pain) and activity in the nucleus accumbens, the striatum or the ventromedial prefrontal cortex (VMPFC), areas all related to (the anticipation of) reward. Increased activity in the insular cortex (pain) as compared to lower levels of activation in the nucleus accumbens would signal that participants experienced too much pain to purchase the good or service, whereas the reverse would signal the participant experienced more feelings of (anticipation of) reward than pain, and would purchase the good or service (Knutson et al., 2007). Research by Plassmann, Mazar, and Rangel (2011) further explored the pain of paying, by contrasting it to the experience of physical pain (electric shocks). They found heightened insular activity during the electric shocks (the insular cortex is mainly associated with physical pain, not psychological pain), but did not find it during the payment process of

an auction, thereby rejecting the idea that the pain of paying has a neural basis. Individual's subjective pain tolerance levels (for both shocks and prices) had been calibrated and matched using a BDM auction mechanism. There not being a significant effect of the pain of paying, or any effect, directly contradicts findings by Knutson et al. (2007). Applying this work directly to the study of payment methods, work by Banker et al. (2017) does not replicate the finding of decreased activity in the rAIC (right anterior insular cortex) but finds heightened activity in the striatum and VMPFC, indicating no change in pain experienced, but an attention shift towards the potential reward of the purchase when paying using credit cards as compared to cash. Additionally, reward network activation weakly predicted cash purchases, and only among relatively cheaper items. This study does show there to be a difference between payment methods, but not with regards to the pain of paying, but the pleasure of purchasing.

In addition to there being an issue with replication of the neural basis of the pain of paying, there is also an issue of causal inference to consider. The insular cortex has not exclusively been linked to the experience of physical pain. It has also been linked to an overwhelming variety of other functions ranging from sensory processing to representing feelings and emotions, autonomic and motor control, risk prediction and decision-making, bodily- and self-awareness, and complex social functions like empathy (Gogolla, 2017). This wide cast net of findings urges us to be critical of perceiving heightened activity in the insular cortex. If there is an increased activity of the insular cortex, it need not be a signal of increased levels of pain.

Moreover, the limited number of neuroscientific studies conducted have exclusively studied the difference between purchasing decisions, with a single study looking at the differences between credit cards and cash. Further research requires to also test other methods of payment, to exclude the possibility that all we are currently seeing is the brain responding to immediate rewards from the purchase and delayed payment due to the non-concurrency of the credit card.

The replication crisis has shown that not all findings and results we deemed to exist were as robust as they were made out to be. Some replicated, some replicated partially, some did not replicate at all. More research is needed to establish whether the pain of paying exists. We are very cautious in associating our findings to the theory of the pain of paying. We do not believe our results to be driven by the pain of paying, and we scrutinize the pain of paying as a concept, as we fail to assess the current body of research as robust.

In addition to the doubt that has arisen considering the pain of paying, we also raise the issue that some of the prior work on payment methods is correlational, and cannot be used to make causal claims. A large number of studies exclusively made use of

a survey methodology (Hirschman, 1979; James, 2017; Raghurir and Srivastava, 2008; Trütsch, 2014; Srivastava and Raghurir, 2002; Zellermayer, 1996), or conducted observational studies (MasterCard US, 2011; Prelec and Simester, 2001; See-To and Ngai, 2019; Soman, 2003) and did not account for individual differences through the application of randomisation. Even when prior work has been (partially) conducted in lab settings and can claim to be causal (Chatterjee and Rose, 2012; Feinberg, 1986; Shah et al., 2016; Thomas, Desai, and Seenivasan, 2011) there is the issue of external validity. Results found in a lab do not always exist in the “real world” (Galizzi and Navarro-Martinez, 2019). Moreover, several of the studies conducted in the lab made use of credit card paraphernalia (e.g. logos, insignia) in their credit card conditions. We wonder whether the presence of credit card paraphernalia is enough to stimulate behaviour equal to actually having to pay by credit card. A criticism which can equally be applied to the studies which stimulated willingness to pay (Prelec and Simester, 2001; Raghurir and Srivastava, 2008; Runnemmark, Hedman, and Xiao, 2015) rather than actual paying: there might be a gap between willingness to pay and what a consumer will actually pay when the moment comes (Barber et al., 2012). We aimed to minimize these limitations in this thesis by applying a mixed methodology, grounded in surveys, observational work, experiments and real world data.

7.3 Contributions

This thesis aimed to contribute to the literature in a number of ways. We have outlined per chapter the contributions we are making to the field of researching payment methods and their effect on various aspects of personal finance management.

In Chapter 3 we conduct two studies showing the effect of contactless payment methods on expenditure recall, showing that contactless payments methods do reduce recall accuracy as compared to cash. Chapter 3 contributes to the literature in multiple ways. First, we introduce a new payment method, contactless payment, to fit within the already existing domain of expenditure recall. We find that contactless payment methods do in fact reduce the accuracy of expenditure recall as compared to cash, for both short-term and longer-term recall, in Study 1 and Study 2 respectively. This provides support for the memory account (Magnussen et al., 1991), indicating that the quickness of the transaction and the reduced exposure to the total amount to be paid associated with contactless payments are enough to reduce expenditure recall accuracy. Second, we establish there to be a difference between contactless cards and PIN-verified cards, in terms of short-term expenditure recall (credit cards) as well longer-term expenditure recall (debit cards). This

finding again supports the memory account proposed by Magnussen et al. (1991) as PIN-verified methods require an additional memory process: the recall of the PIN-code, which may negatively impact expenditure recall. Third, we study the mechanism underlying the differences in expenditure accuracy caused by different methods of payment and support the results found by Banker et al. (2017) that the underlying mechanism is not the prominent theory of the pain of paying. We do not find the pain of paying sufficient in explaining differences in expenditure recall, we do not find different levels of pain of paying for different payment methods, nor do we find a mediation effect. This chapter shows there to be both a correlational (Study 1) and causal (Study 2) impact of payment methods on expenditure recall, but the underlying mechanism remains unknown.

In Chapter 4 we conduct an analysis of transaction data provided by a Financial Aggregator App to establish the effect of the onset of contactless usage on a variety of personal finance measures, contributing to earlier empirical work in several ways. First, it shows that contactless payment methods do fit the already existing theories on paying, but not seamlessly. With regards to spending they adhere to the predictions made by theories such as the pain of paying and transparency, which was their primary purpose. A significant increase in spending, in both volume and value, is associated with the onset of contactless usage. When looking into the effects of contactless usage associated with overdraft fees, debt, cash usage and savings, the fit is no longer as seamless and we find the aforementioned theories insufficient in explaining the changes we find in personal finance management associated with the onset of contactless usage. Second, we show that the onset of a new payment method on one account changes how that account is used. Our results show that the use of contactless payments on one account directs more attention and financial dealings to this account. There is no suggestion in prior literature that this shift would occur, nor why it would occur. Third, this research is unique in its methodology. Most of the prior work reviewed did not make use of third party data, most of the previous studies are grounded in lab work or survey responses. Fourth, we use a large sample based in the UK, rather than the US. The advantage here is that contactless payments have become normalised and popularised within the UK payment landscape, whereas this has not yet occurred in the US. Fifth, we provide an overview of the effect of one new payment method, contactless, on a multitude of variables, rather than exclusively focusing on one aspect such as spending. Additionally, we provide analyses on both the user and the account level, painting a more detailed picture of the effect of contactless payments on personal finance management. Last, finding that the effect of contactless on debt occurrence, measured in overdraft fees, unsecured loans and credit card debt, is not as big as postulated by payment theories, or rather, is not present at all in these data, is a relief, given the level of societal acceptance of this payment method (UK Cards

Association, 2019; UK Finance, 2021). It is also a relief that cash still has a fighting chance, given that a reductions in either volume and value were not of the magnitude expected, nor of the direction expected. Cash remains to be a commonly used method of payment, which is good, given its budget-friendly constraints (Doyle et al., 2017).

In Chapter 5 we conduct an analysis of transaction data provided by a Financial Aggregator App to establish the effect of the onset of mobile payments, an even more novel payment method, on a variety of personal finance measures, contributing to earlier empirical work in several ways. First, we contrast two accounts of theories, simplicity and salience, to explain the possible effects of mobile payments on personal finance management. The simplicity account is based on theories such as the pain of paying (Zellermayer, 1996) and transparency (Soman, 2003) arguing that as payment methods become simpler, quicker and less physical, the transaction becomes less salient. The salience account is based on mental accounting (Thaler, 1999), arguing that mobile payments increase the salience of transactions as mobile devices send out notifications after each transaction, and are also associated with expenditure tracking. We show that mobile payment methods do not fit the simplicity account, rather, we find more evidence to support the salience account, finding that the onset of mobile payment usage improves personal finance management by increasing cash usage and savings, having no impact on debt and reducing overdrafts. This result is specifically interesting in the light of the findings in Chapter 3, which do not support an account of the pain of paying being the mechanism driving expenditure recall. Second, similar to Chapter 4, we show that the onset of a new payment method on one account changes how that account is used. Our results show that the use of mobile payments on one account direct more attention and financial dealings to this account. There is no prior research showing that the onset of a new payment method on one account leads to a change of usage of that account. This is an interesting finding as it could provide a new way for financial institutions to motivate their customers to use their accounts, by offering them novel ways of paying. In line with the contributions made in Chapter 4, Chapter 5, due to a similar methodology, contributes to the prior literature by making use of third party data, rather than lab or survey work, raising the external validity of the work. We paint a more complete picture analysing both the account and the user, as well as providing an overview of the effect of one new payment method, mobile payments, on a multitude of variables, rather than exclusively focusing on one aspect such as spending. Additionally, our sample is based in the UK, where mobile payments have become normalised and popularised, whereas this has not yet occurred to the same extent in other countries, such as the US. Last, finding that the effect of mobile payments on debt occurrence, measured in overdraft fees, unsecured loans and credit card debt, is not as big as postulated by payment theories proposed by the simplicity account (Garrett

et al., 2014; Meyll and Walter, 2019), is a relief, given the level of societal acceptance of this payment method (Statista, 2020d). It is also a relief that cash still has a fighting chance, given that a reductions in either volume and value were not of the magnitude expected, nor of the direction expected. Cash remains to be a decently popular method of payment, which is good, given its budget-friendly constraints (Doyle et al., 2017).

In Chapter 6 we establish a link between payment methods, spending distributions and personal finance management. We assume that the effect of payment method is no longer direct, but indirect, and that the changes in behaviour are due to a change in the spending distribution, caused by the payment method. This chapter contributes to the prior literature by showing that shifts in the spending distribution do indeed change people’s abilities to manage their personal finances (Study 1), as well as their ability to estimate the total of a distribution (Study 2). We find that the length of the spending distribution (number of transactions, number of stimuli) as well as its skew predict the ability to correctly track expenditures. An increase in length and skew being associated with higher spends, increased overdraft usage, more debt and less savings (Study 1), as well as higher levels of underestimation of the totals (Study 2). This indicates that changes in the spending distribution also have an effect on personal finance management and expenditure estimation and that there may be more indirect or mediating effects that we were unaware of as of yet. These changes in the spending distribution caused by payment methods, such as increased spending volume, have been corroborated by prior work (James, 2017; MasterCard US, 2011; See-To and Ngai, 2019; Trütsch, 2014) as well as our own work (Chapters 4, 5). Second, we contribute to the few papers that have looked at the underlying characteristics of a numerical distribution, and their effect on estimation. Our findings are only partially in line with those by Scheibehenne (2019) and Van Ittersum, Pennings, and Wansink (2010) who also find a tendency towards underestimation, but find that the underlying characteristics of the distribution do not matter. We, on the other hand, find that both skew and the number of items (transactions, stimuli) significantly impact both personal finance management (spending, debt, savings), as well as the accuracy of estimating the total of a spending distribution. Moreover, we also find a significant, but lesser, role for measures such as kurtosis, the fifth moment, as well as count variables indicating the number of stimuli of a value of over one hundred. We reject the idea that the underlying characteristics of a distribution do not matter. Last, we show these effects using both real world transaction data and an online study. This mixed methodology enables us to establish a causal link, as well as produce results with high external validity.

As a whole, this dissertation contributes to the literature by first, studying two relatively new payment methods, contactless and mobile, and fitting them into existing

frameworks of paying. And second, by applying a variety of methodologies to study them. Prior work has focused almost exclusively on applying a singular methodology (e.g. lab work) to approximate the effect of payment methods. In this dissertation, we employ observational studies, survey work, third party data as well as online surveys and experiments with randomisation. This allows our work to make both causal claims and have high levels of external validity. Third, we examine the effect of payment methods on a multitude of variables related to personal finance management (total spending, frequency of spending, expenditure recall, debt occurrence, savings, cash usage) rather than focusing on these effects in isolation, as most prior work has done. Fourth, we scrutinize the existing frameworks of paying, predominantly the pain of paying, and contribute to the research debating its existence, or at least its efficacy, in explaining the different behavioural outcomes associated with different payment methods. We do so by not finding a direct or mediation effect of the pain of paying in Study 2 of Chapter 3, and finding more support for the salience (mental accounting) account for mobile payments rather than the simplicity account which encompasses the pain of paying as a theory in Chapter 5. We also raise some serious doubts surrounding the already existing evidence supporting the existence of the pain of paying. Fifth, to further scrutinize the existing frameworks and underlying assumptions with regards to the effect of payment methods on personal finance management, we examine the possibility of an indirect impact of payment, where the use of different payment methods lead to a shift in spending distribution which in turn leads to differences in personal finance management. We find that the main effects impacting personal finance management (spending frequency and value, various forms of debt and savings) are skew and length (number of transactions). We support this correlational finding by an online experiment, replicating our results, showing a now causal link between the accuracy of expenditure estimation and skew and length. Again, our mixed methodologies provide us with additional robustness. Sixth, this dissertation highlights issues that warrant further studying, the issues centering around mixed methodologies, underlying mechanisms, endogeneity, causal inference and the spending distribution. We discuss these in turn in the next section.

7.4 Further Research

In addition to contributing to prior work, this thesis also proposes several avenues of new research. We wonder whether prior work has sufficiently accounted for the endogenous factors we have accounted for, such as being on a budget, being a tightwad and has made use of random allocation of payment methods to study the effect (Chapter 3).

We strongly suspect that people with different individual characteristics opt in to using different payment methods, e.g. spendthrifts may opt-in to using credit cards as they make it easier to spend, which is exactly what a spendthrift wants, as they like spending money. For tightwads, the opposite would hold true: they would opt in to using cash, as cash is known for restricting spending, in line with the preferences for tightwads. The opposite might also hold true: if we assume our consumers to be sophisticated, spendthrifts, knowing their desire to spend, may opt in to using cash to curb their own spending, whereas tightwads may opt in to using payment methods that make spending easier, such as the credit card, to reduce their aversion of spending during the transaction itself. This, however, remains speculation and warrants further research.

The concept of the pain of paying warrants further research as a whole. The longstanding idea of credit cards having reduced pain of paying was recently rejected by Banker et al. (2017). They found that shopping with credit cards did not lead to lower pain of paying (exaggerated deactivation in the rAIC) during a transaction. Instead, they found that credit cards appeared to generally facilitate greater reward sensitivity (heightened activity in the VMPFC and striatum), rendering consumers less sensitive to price information. When price information becomes less sensitive, it reduces salience, and memory will struggle to encode the price and the total amount spent. This is different from the pain of paying account, and in line with our findings for both expenditure recall with contactless, as well as the findings in Chapter 5 on the onset of mobile payment usage. This does alter the approach required to establishing the mechanism behind the behavioural differences when using different methods of payment. We may not be looking for pain, we may be looking for the opposite: pleasure. If it is increased reward sensitivity and reduced price sensitivity that matter, the field will have to rethink its approach to the psychology of payments. Throughout this thesis we have questioned the validity of the research underlying the pain of paying as a concept, as there are issues with self-reported measures (Rosenman, Tennekoon, and Hill, 2011), priming (Locke, 2015) as well as the causal inferences made by neuroscientific studies (Plassmann, Mazar, and Rangel, 2011; Knutson et al., 2007). In addition to these issues, the pain of paying has almost exclusively been tested in an online shopping environment, with only a single study looking at payment methods, contrasting transactions made by cash and those made by credit card. Further research should focus on whether the pain of paying is also experienced when using concurrent payment methods such as contactless debit cards and mobile payments, both behaviourally and neurologically. And whether the pain of paying exists at all.

Despite research on payment methods slowly increasing, most research has focused on one aspect, such as spending (**mastercard**; Feinberg, 1986; Hirschman, 1979; James, 2017; Prelec and Simester, 2001; Runnemark, Hedman, and Xiao, 2015; Soman, 2003;

Tokunaga, 1993; Trütsch, 2014; See-To and Ngai, 2019) or debt (Garrett et al., 2014; Gross and Souleles, 2002; Lee, Abdul-Rahman, and Kim, 2007; Meyll and Walter, 2019). Although several theories have been proposed to explain why different payment methods lead to different behaviours (e.g. the pain of paying (Zellermayer, 1996), transparency (Soman, 2003), decoupling (Raghubir and Srivastava, 2008) and multi-functionality (Gafeeva, Hoelzl, and Roschk, 2018)), these theories always assume a direct effect of payment method, often exclusively on spending. Later research has extended these theories to also fit explanations of reduced expenditure recall accuracy (Gross and Souleles, 2002; Raghubir and Srivastava, 2008; Srivastava and Raghubir, 2002), reduced impulse control leading to more frequent spending (See-To and Ngai, 2019; Thomas, Desai, and Seenivasan, 2011), and debt accumulation (Gross and Souleles, 2002; Lee, Abdul-Rahman, and Kim, 2007). It is plausible, however, that the effects beyond spending are indirectly, rather than directly, caused by payment methods, and warrant further research to understand the mechanisms underlying these effects. We have tried to do exactly that in this research, but more research is needed to uncover the underlying mechanism that may be driving these behavioural outcomes, and as such warrant further studying, with a critical approach to the assumption that it is the payment method itself driving the behavioural outcomes seen.

In addition to further understanding the workings of both endogeneity and the potential underlying mechanisms of payment method, we have to go beyond the payment methods as they currently stand. Neither contactless payment methods nor mobile payment methods are the most recent payment method to be introduced, yet research on these methods is already scarce. Especially as newer payment methods become increasingly faster available, and the pandemic and lock-downs have shifted the majority of spending online. We need to gain a better understanding of how these changes, in both methods and settings, change the perception of money and the effect this may have on personal finance. Is it possible that the introduction of a “quick and easy” payment method changes how we feel about spending money? Or about how we relate to money in general? Research has indicated that as payments become easier and quicker, that they are less painful and less salient (James, 2017; Soman, 2001; Prelec and Simester, 2001; Raghubir and Srivastava, 2008; Zellermayer, 1996). However, there has been no research so far to see what the longer term effects of these changes in salience are for how we relate to money, and spending money.

In line with the previous suggestion, there has been little to no research showing whether there is a difference between how people relate to money, and manage their personal finances, depending on which method they learned to manage money. Several younger generations learned about money not through using cash, but through e-money,

online banking and holding payment cards, whereas older generations were taught about money through cash, the physical representation of money. Identifying the mechanisms which make for better personal finance management might be related to which payment method, physical or electronic, we grew up using, as a physical form of money does convey a different psychological construct than a non-physical form does (Trope and Liberman, 2010). We are aware of the longitudinal design of this study, as well as a variety of confounds that need controlling for. We do not think this will be an easy study to conduct, having to account for a variety of personality, individual, endogenous factors as well as external factors and confounds, but do think such a study would be very impactful in understanding the relation between payment methods, personal finance management and perceptions of money.

Moreover, we have hypothesized and shown that the onset of using a new payment method can shift spending from a non-enabled account to the enabled account. This is a plausible explanation for the increased spending and savings we find in Chapters 4 and 5, in line with research by Krol et al. (2016) who showed that easier methods are preferred to more difficult payment methods such as cash. However, there has been no research showing that there should be a shift in account usage, nor an empirical verification of why this shift would occur. It would also be interesting to see how consumers would react if all of their spending accounts had different payment methods enabled on them (e.g. one credit card account, one mobile enabled account and one contactless card enabled account). Research should look at how this would affect account usage and whether there would still be a compensation mechanism at play, or, whether such a portfolio of payment methods would severely worsen personal finance management due to a complete loss of oversight.

Last, we have raised questions as to the impact of Financial Aggregator Apps on (mental) accounting and accurate expenditure tracking. In Chapter 5 we found no effect of logging into the Financial Aggregator App on personal finance management. However, the results in Chapter 5 also indicate that the multi-functionality (Gafeeva, Hoelzl, and Roschk, 2018) of the mobile device supports mental accounting (Thaler, 1985), and reduces the effects of the payment method on variables such as spending, both in frequency and value. Research by Huebner, Fleisch, and Ilic (2020) has shown that the mere presentation of transactions and transaction values was not sufficient to change financial behaviour and research by Pocheptsova Ghosh and Huang (2020) has shown that the presence of balance information stimulated spending, rather than prohibited it. These contrasting findings require further research. This research would be interesting for both academics, policy makers and those working in the financial technology (fintech) industry, to understand how consumers consume financial information, to find which features

should and should not be promoted in these apps, and to create the most optimal version of a Financial Aggregator App, to the benefit of the consumer.

7.5 Conclusion

This thesis has aimed to expand the existing payment frameworks to include newer payment methods, contactless and mobile, and to analyse their impact on various measures of personal finance management, through a mixed methodology approach. We have examined both the direct effects of payment methods, as well as having linked payment methods to changes in the spending distribution, thereby indirectly, rather than directly, impacting personal finance management. We have found there to be direct effects of payment methods: contactless payment methods significantly reduce the accuracy of expenditure recall (Chapter 3), and significantly increase spending (both value and frequency), as well as cash usage and savings, although the latter result is explained by a change in account usage (Chapter 4). Mobile payment methods were found to significantly increase spending frequency, and also significantly reducing various forms of debt. Again, we found a significant increase in cash and savings, most likely due to a change in account usage (Chapter 5). We also found there to be an indirect effect of both mobile and contactless payments as they increased the spending frequency, changing the set length of the spending distribution, and as postulated by prior work, increased the skew of the spending distribution, favouring smaller impulse spends, which then impacted personal finance management (Thomas, Desai, and Seenivasan, 2011). Placing our findings in the context of prior work, we do not find support for the pain of paying as a driving mechanism, and question its validity in explaining the differences in behavioural outcomes associated with different payment methods. We strongly recommend further research to be done in this area, both behavioural and neuroscientific research, in establishing whether the pain of paying exists, and whether it plays a role in the behavioural outcomes associated with different payment methods. In general, we urge research to study a wider variety of payment methods, as a large body of work has exclusively focused on credit cards. We also strongly urge this field of research to apply mixed methodological research, to study the entire spectrum of payment methods as well as focus on a multitude of dependent variables when doing so, whilst also accounting for endogenous factors such as the individual's position on the spendthrift-tightwad-scale and their financial situation. Additionally, we would like to see work that contributes to the general perception of money, and how it changes as newer, quicker, and easier payment methods are introduced.

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