Essays on Individual Decision Making in the Field

by

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Thesis

Submitted to the University of Warwick

for the degree of

Doctor of Philosophy in

Economics and Psychology

Department of Psychology

September 2018

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Acknowledgements

I am immensely grateful to my supervisors Neil Stewart and John Gathergood for providing plenty of help and encouragement during the last years. I could not have gotten better supervisors. Neil, thanks for the many technical discussions we had—you certainly influenced my view about null hypothesis significance testing—and for creatively suggesting the titles for my papers. Most of all, thanks for letting me be entertained with enough research projects to never get bored during my PhD studies. Here, we have some examples of the exciting research I have done. John, thanks for reviewing meticulously all my work and always offering sensible and pragmatic advice. Thanks for setting high standards to my work too—writing “a line of code” was a lot of fun∼.

I also want to thank Professor George Loewenstein (co-author) for his contribution, helpful comments, and discussions to the paper presented in Chapter 3.

I met some very good friends who made my PhD journey more enjoyable. Thanks for the good time Sakinah, Naili, Suha, Alisa, Kim, Massa, Jenny, Ameerah, Karla, and Ai among others. Naily, thanks for the company during long sleepless hours at the library. Sakinah, thanks for the tremendous support and kindness. Special thanks to my colleague and friend Hiro, with whom I have spent many long hours discussing data cleaning strategies for big financial data.

I must thank my parents and my brother for understanding my career path and goals and for their unconditional support, patience, and care during all these years.

Finally, I would like to thank the financial support I received from the Economic and Social Research Council to undertake this PhD.

Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy in Economics and Psychology. It has been composed by myself and has not been submitted in any previous application for any degree.

The work presented (including data generated and data analysis) was carried out by the author as detailed below.

Chapter 2: Bad cop, bad cops: Learning and peer effects on police misconduct

Chapter 2 is co-authored with Neil Stewart (WBS, University of Warwick). Data were provided by the Metropolitan Police Service to Stewart. The concept for the paper was developed jointly by the authors. Quispe-Torreblanca designed and completed all the analysis, and wrote the manuscript of the paper. The authors subsequently made many edits. A revision of the paper has been requested by Nature Human Behaviour.

Chapter 3: The red, the black, and the plastic: paying down credit card debt for hotels not sofas

Chapters 3 is co-authored with Neil Stewart, John Gathergood (School of Economics, University of Nottingham) and George Loewenstein (Department of Social and Decision Sciences, Carnegie Mellon University). Data were provided by Argus UK to Gathergood and Stewart. The concept was suggested by Stewart, and developed jointly by the authors. Quispe-Torreblanca designed and completed all the analysis, and wrote the first manuscript of the paper. Subsequently, all authors made many edits, incorporating the comments from reviewers. Following a reviewer's suggestion, the authors developed a survey. Stewart ran the survey and Quispe-Torreblanca completed its analysis. The paper is currently in press at Management Science.

Chapter 4: You only watch when you're winning: Selective attention among individual investors

Chapter 4 is co-authored with Neil Stewart and John Gathergood. All authors jointly developed the concept. The data were provided to Stewart by Barclays. Quispe-Torreblanca designed and completed all of the analysis. Gathergood wrote much of the first draft of the paper based upon a detailed plan developed in correspondence between all of the authors, to which Quispe-Torreblanca contributed substantially. Quispe-Torreblanca has made an extensive contribution to the writing in subsequent edits. The paper is to be submitted.

Chapters 1 and 5 were written entirely by Quispe-Torreblanca with minor edits from Stewart and Gathergood.

List of publications including submitted papers:

- Quispe-Torreblanca, E.G. and Stewart, N. (submitted). Bad cop, bad cops: Learning and peer effects on police misconduct. Revision requested by *Nature Human Behaviour*.
- Quispe-Torreblanca, E.G., Stewart, N., Gathergood, J. and Loewenstein, G. (in press). The red, the black, and the plastic: paying down credit card debt for hotels not sofas. *Management Science*.

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Abstract

This thesis consists of three independent studies in the field of behavioural and economic science. The aim is to provide a better understanding of individual decision making using large field datasets and the techniques from econometrics. Chapter 1 introduces the relevant literature. Chapter 2 investigates deviant behaviour among police officers. It addresses two questions: What is the effect of corrupting colleagues on officers' misconduct? Can misconduct be deterred by sanctions? By analysing data from 50,000 officers, we show that officers learn to reduce their own risk of misconduct but that misconduct amongst their peers increases their own risk of misconduct.

Chapter 3 analyses how mental accounting influences intertemporal choices in credit card repayment. We test the major prediction of Prelec and Loewenstein's (1998) theory of mental accounting: that consumers will pay off expenditure on transient forms of consumption more quickly than expenditure on durables. Using data from 1.8 million credit card accounts, we provide the first field evidence in support for this prediction.

Chapter 4 discusses how investors pay selective attention to their portfolios. We use a rich dataset containing investors' daily login and trading activity. First, we study whether investors deliberately reduce their attention to negative news (demand side for attention). Second, we evaluate how changes in the opportunity cost of attention affect investors' login activity (supply side for attention). We use weather shocks as an exogenous source of changes in the opportunity cost of attention. Our results show that when investors anticipate that their portfolio has dropped in value, they regulate the hedonic pain of negative news by logging in less often. Also, on sunny days, they substitute viewing their portfolio for other less costly leisure activities.

We conclude with some comments and future directions for the endeavour of addressing questions in psychological science with big datasets combined with the techniques from econometrics.

Chapter 1

Introduction

Classical economic theory assumes that economic agents are rational. However, increasing experimental evidence shows that individuals deviate from the assumptions of standard economic models (Fehr et al., 2002; Kahneman and Tversky, 1979, 1984; Thaler, 1985, 1990, 1999). Much of this evidence comes from psychologists and experimental economists who have gained expertise in the development of well-controlled laboratory experiments that were designed to reveal the fundamental mechanisms underlying human behaviour and cognition, prompting us to rethink normative economic theory. However, the recent and growing availability of large sets of behavioural data, such as transaction data, mobile data, social media data and so on, represents a promising new direction for the discovery of regular deviations from normative theory.

I believe that this diverse range of data sets provides unprecedented opportunities to test whether violations of rationality extend to the field. Thus, in this thesis, I move beyond studying decision making in the lab and attempt to reveal field evidence of behavioural anomalies. My approach continues the line of work that uses case studies to uncover principles of judgment and decision-making. To mention some examples of research in the field, there is the work of Lacetera et al. (2012), who explore whether the tendency to focus on the left-most digit of a number (left-digit bias) influences purchase decisions. After analysing over 22 million used-vehicle transactions, they provide evidence of discontinuous drops in vehicle sales prices at 10,000-mile and 1,000-mile thresholds in odometer mileage. Hastings and Shapiro (2013) show, on the other hand, that households do not treat 'gas-money' as fungible. When gasoline prices rise, many customers substitute higher grade gasoline to lower grade gasoline to a degree that cannot be explained by income effects. There is also the work of Bhargava et al. (2017), who examine the health plan choices of about 23,000 employees at a U.S. firm and find that the majority of employees choose dominated plans, a pattern that cannot be accounted by standard risk preference or any expectations about health risk. Instead, the popularity of dominated plans is driven by the failure of consumers to accurately evaluate and compare plans. For an extensive review of cases that document aspects of behaviour that deviate from the predictions of the standard theory, see DellaVigna (2009).

In this thesis, I present three independent essays that document (i) evidence of negative peer effects in police misconduct, (ii) evidence of systematic violations of fungibility in consumer credit card repayment choices, and (iii) evidence of active information avoidance among investors. I use large panel data sets and the appropriate econometric techniques to control for variables that may mask the underlying relationships of interest. Much of my discussion will focus on reporting stylized facts in order to make the empirical analysis of our data more pertinent given that laboratory experiments have already provided insights into some possible causal relationships.

The rest of this chapter takes the following format. First, I present a brief overview of the literature pertinent to each essay. This overview aims to introduce the relevant literature to the chapters that follow and does not constitute a comprehensive revision of the work in the field. More detailed literature reviews are, however, given at the start of each chapter. The outline of the thesis is presented at the end of this chapter.

1.1 Police Ethics and Deviance

Chapter 2 is structured around the following issues: first, how police misconduct spread? Second, how responsive are police officers to the threat of discipline for their inappropriate behaviour? And third, what are the challenges and limitations in studying police misconduct in the field?

There is substantial interest in the study of why people engage in unethical behaviour. In fact, during the last three decades, a growing body of literature has started to recognize key individual-level and contextual-level drivers of unethical decisions, such as the individuals' cognitive moral development, peers and leadership influences, codes of conduct, and the ethical climate (for a review, see Treviño et al., 2014). Among these drivers, and in the study of misconduct in organizations, we are particularly interested in how misconduct spreads: Do bad apples spoil the bunch?

Conceptually, people making decisions inside organizations are subject to authority rules and regulations, social norms, cultural expectations, and potentially large peer-group pressures. Kohlberg's research on moral reasoning (1969) has shown that unlike childhood (when children were more concerned about the physical consequences of their actions, i.e., punishments and rewards, and when elements of reciprocity and fairness started to be incorporated pragmatically), moral reasoning in adolescence and adulthood is typically determined by beliefs about what others will think is right or wrong. In this level of moral thinking (termed as 'conventional' by the author), the individuals try to conform to the natural or accepted behaviour.

A great deal of previous research has, in effect, provided compelling evidence for the existence of peer effects under different labels (herd behaviour, conformity, social interactions, spillover effects, contagion, and so on), and making use of models that incorporate rational and/or irrational motives, such as social learning, strategic interactions and behavioural biases. In the financial literature, for instance, herding behaviour by investors can be thought as an irrational reaction driven by emotion, greed and fear, that pushes individual investors to join the crowd of others. Or it can be thought as a rational response induced by imperfect information, concerns for reputation and compensation structures (Bikhchandani and Sharma, 2000).

Although peer influences have been subject to analysis in various domains via both lab and field studies (Herbst and Mas, 2015, provide a recent meta-analysis of peer effects in co-worker productivity comparing peer effects from laboratory experiments and peer effects from naturally occurring environments and show that laboratory studies generalize in the real world), surprisingly, much uncertainty still exists on the influence of peers on unethical behaviour in the field. In particular, much more empirical work is needed for the understanding of peer effects in police ethics and integrity. Observe that unlike other organizations, the police are empowered to enforce the law and protect individual liberties, and so the integrity in policing is essential for establishing and maintaining legitimacy, as is the integrity of other agents involved in the criminal justice system (Rosenbaum, 2016).

Because evidence on peer effects in police misconduct remains speculative and largely restricted to cross-sectional studies, in the first part of this thesis, we attempt to provide, to our knowledge, the first clear evidence of peer effects.

Specifically, we are the first to establish causality in peer effects in police misconduct, rather than mere correlation. We aim to quantify the extent to which a bad cop would spread misconduct. With this objective in mind, in Chapter 2 we analyse misconduct records maintained by the UK Metropolitan Police Service for nearly fifty thousand police offices. The longitudinal data available to us covers five years of allegations of misconduct, from 2010 to 2015, and allows us to recognize teams of individuals by linking officers assigned to the same line manager. Therefore, it provides us with a rare opportunity to investigate peer effects when officers are assigned to different teams.

What follows is a brief discussion on the organisational processes and structures that shape the ethical climate in any given police force. A recent review by Hough et al. (2018) identifies five organizational factors that shape individuals' ethical decision-making in police organizations: the formal codes of conduct, the selection and training procedures, the systems for performance management, the organisation's values and culture, and the style of leadership. The influence of these factors is suggested to be mediated by situational variables, such as the individual differences between decision-makers, the presence or absence of ethical challenges, and the presence or absence of corrupting colleagues. While existing research has already provided important insights into the effects of police departments' characteristics and some individual demographic characteristics on the likelihood of misconduct events, the problem of corrupting colleagues has received scant attention in the research literature. It is, therefore, the first issue we examine in Chapter 2.

We should note, however, that our analysis of peer effects in police ethical behaviour does not intend to engage in the debate of what specific mechanisms are driving these effects, nor our data allow us to distinguish, for instance, between social influences motivated by learning via gathering information about what behaviour is best to follow given the individuals' own needs, or motivated by pure peer pressure and social conformity. In fact, most research in the peer effects literature have focused on measuring the magnitude of peer effects only and have focused less upon the mechanisms that may be producing the peer effects due to the difficulty to discriminate between such mechanisms.

While a discussion of the mechanisms behind police peer effects is beyond the scope of our research, it is worth commenting on the most recent findings in the literature provided by Hough et al. (2018). The authors examined cases of alleged misconduct involving chief police officers in England and Wales over a six-year period, up to 2013, and interviewed stakeholders, police officers and other personnel who had investigated chief officers misconduct. Their interviews suggest that, throughout their careers, police officers felt under pressure to not step outside the norm. The ethical climate, promoted by a typical command-and-control style of management, is alleged to lack ethical values or, even worse, to sustain the wrong kinds of values. The command-and-control style of management appears to encourage close mutually supportive and inward-looking networks that favour homogeneity, preclude difference and even accept or tolerate bullying behaviour.

As stated, instead of examining the nature of peer effects and exploring some of the above highlighted mechanisms, the added value of our research is to properly quantify these effects (if any indeed exist). Establishing causal peer effects is empirically challenging because peers influence each other simultaneously and because there are common unobservable factors that affect simultaneously the members of the same peer group and, thus, mask real peer effects Manski (1993). In Chapter 2, by using instrumental variable techniques, we address these issues and report statistically significant and nontrivial peer effects. Specifically, we exploit the variation in peer quality that results when officers change line managers and switch peer groups. Misconduct of the new peers acquired following the change is instrumented with prior events of misconduct of their new peers' peers, a strategy that enable us to estimate the causal effect between peers.

After examining the effect of corrupting colleagues in police misconduct, the second questions we address in Chapter 2 is whether misconduct can be deterred by sanctions. Although it is intuitive that punishment influences ethical behaviour in organizations and in fact existing research on deterrence recognizes that both the perceived risk of being sanctioned and the sanctions' severity lowers the recurrence of illegal activity (Nagin, 1998), the evidence of the deterrent effect of the sanction threats for police misconduct is largely speculative and sometimes counterintuitive. For instance, Pogarsky and Piquero (2004) conducted a survey about police misconduct to 210 police officers from a southwestern United States police department and found that the perceived sanction severity offered little deterrent threat. Only perceived sanction certainty and perceived sanction celerity were negatively associated with police misconduct. Notably, extra-legal or informal sanctions, such as social disapproval or embarrassment, appeared to be a strong deterrent against misconduct. More counterintuitively, Harris and Worden (2014) examined personnel complaints against 1,356 patrol officers from a police department in the northeaster United States and identified that officers who received more severe sanctions were more likely to receive an additional sustained complaint when compared with no sanctioned officers. The authors provide three hypotheses to explain such counterintuitive results: punishment could be an indicator of the most active offenders that are less likely to be deterred; those punished mistakenly believe that the punishment experience prevents them from future apprehension on the next offenses (since sanctions are relatively rare, they reset their sanction certainty, as in the gambler's fallacy); or those punished might perceive the sanctions as unfair, which ultimately prompt them to defy and thus increase offending. Although the authors could not discriminate among these alternative hypotheses, they argue that the most plausible explanation is the perceived injustice of the disciplinary system that may encourage officer deviance.

Since these findings are controversial and since police disciplinary systems are grounded on the notion of deterrence, in the second part of Chapter 2, we investigate the effects of the severity of the sanctions received after alleged cases of misconduct. Unlike previous research that analysed the effect of sanctions on the likelihood and timing of complaints filed against officers ignoring individual heterogeneity, we test the deterrent effect of the sanction threats via a dynamic model that explicitly accounts for individual (time invariant) differences. Note that a major drawback of the related literature is the failure to account for individual differences. Yet, it is known that because of some latent and enduring personal characteristics, individuals' probabilities to engage in misconduct differ, which is evident by the fact that a large number of cases of misconduct are accounted by a small group of officers. The propensity to commit crime is, for example, related to lack of self-control, risk taking behaviour, impulsivity and low conscientiousness (Nagin and Paternoster, 1991, 2000). When this latent characteristics correlate with certain sanction types, estimates of the sanctions' deterrent effects are confounded. We show that standard models that ignore individual heterogeneity are intrinsically flawed. Evidence from our larger dataset suggests that only severe formal sanctions have some deterrent effect. Other disciplinary actions, such as management actions, or no actions at all, do not appear to diminish misconduct events.

1.2 Mental Accounting Theory

We now move on to discuss how individuals make economic decisions, such as what to buy, how (and when) to pay for it, or how much to save. In this section, I address how decisions are made under the mental accounting theory proposed by Thaler (1985, 1990, 1999) and, fundamentally, how mental accounting affects intertemporal choices, following the double-entry mental accounting model proposed by Prelec and Loewenstein (1998).

Research on mental accounting theory (see Thaler, 1999, for a review) describes the way decision makers organize, evaluate, and keep track of their expenditure; that is, it describes the cognitive processes used to perform mental accounting operations in order to keep spending under control. In the decision theory literature, mental accounting concepts have long been used to explain human behaviour that often appears irrational (Kahneman and Tversky, 1984; Shefrin and Thaler, 1988; Thaler, 1980).

A key normative principle of rational choice in microeconomic theory is fungibility. Fungibility implies that money has no labels and so people treat their resources, wealth and any asset as fungible or interchangeable. Mental accounting challenges this assumption because money in one mental account is not a perfect substitute for money in another account. Accounting decisions, such as which account to assign the transactions to or how frequent to balance the accounts, are not neutral. They affect the attractiveness of alternative actions and therefore they affect consumers' choice.

What follows in the next paragraphs is a discussion on two components of mental accounting theory: how outcomes from individual transactions are perceived and evaluated, and how activities are assigned to certain mental accounts. This discussion is largely based on the review presented by Thaler (1990), who illustrates how mental accounting rules influence individual choice, reporting research conducted over two decades on decision making and framing susceptibility.

1.2.1 How Are the Outcomes of Financial Transactions Evaluated?

Under classical economic theory, people make financial decisions, such as what to buy, when to buy, how to pay for it, or how much to save, taking into account their current wealth, their future earnings, the opportunity costs and, in general, all relevant financial information available to them. Kahneman and Tversky (1984) refer to this wealth-based decision-making analysis as comprehensive. We should expect that if decision makers follow this comprehensive reasoning, the context of the choice should be neutral (i.e., framing should not alter choices). But, empirically, decisions may be heavily context-dependent. In the real world, because people make decisions piecemeal rather than all at once, framing does influence peoples' judgments and choices.

The following example is a typical illustration of the framing effect. As part of a series of experiments, Kahneman and Tversky (1984) asked participants to imagine that they had decided to see a play and had already paid $10 for the ticket. However, the day of the performance when they entered the theatre, they discovered that they have lost the ticket. Would they be willing to pay other $10 for another ticket? Most people (54%) refused paying for a new ticket. Nevertheless, when a slightly different version of the problem was presented, these results reverted. This time, participants were only told that have decided to see a play but during the day of the performance, when they entered the theatre, they realized that they have lost a $10 bill. Would they still be willing to pay $10 for the play? Now, more than 80% of the participants were willing to buy a new ticket. The puzzle is why losing the ticket in the first scenario was coupled to the choice of buying a new ticket whereas losing the $10 bill in the second scenario was not. The authors explain this puzzle arguing that mental accounts are topical rather than comprehensive. When the outcomes of any potential choice are framed in terms of topical accounts, they are evaluated in relation to a reference level that is determined by the context within which the decision takes place. In this example, buying a new ticket is a transaction posted to an account that links the cost of the ticket with the experience of seeing the play. Buying a second ticket increases the cost attached to this account. The loss of cash, however, has no influence on the purchase of the new ticket because it is posted to a different account.

Let us now consider in more detail how people combine multiple outcomes within a single account. Thaler's model of mental accounting incorporates the following elements. Outcomes are perceived and coded in terms of the value function proposed by Kahneman and Tversky's (1979) prospect theory. This value function is described over gains and losses relative to some reference point. It shows diminishing sensitivity for both gains and losses; and it reflects loss aversion. Given this value function, outcomes are evaluated according to certain rules of hedonic framing: segregate gains, integrate losses, integrate smaller losses with larger gains, and segregate small gains from larger losses. Intuitively, these rules are assumed to reflect how decision makers would like the world to be organized, that is, how outcomes or events should be edited to make decision makers feel as happy as possible with their decisions. They would prefer, for instance, many small gains to a single large gain because of the diminishing sensitivity of the value function. They would prefer to avoid losses whenever possible but, otherwise, they would combine them, again because of the diminishing sensitivity in the value function.

Under this framework, how the purchase of a product should be coded to be hedonically efficient? Because of loss aversion, Thaler (1985, 1999) discards the possibility that the payment of the product could be framed as a loss. Rather, he suggests that the purchase of the product produces two kinds of utilities: an acquisition utility and a transaction utility. The value of the product relative to its price is reflected by the acquisition utility; whereas, the value of the deal (i.e., the difference between the price expected by the customer and the actual price paid) is measured by the transaction utility. To illustrate the effect of incorporating a transaction utility in the coding of the purchase, consider the following experiment. Thaler (1985) asked participants (regular beer drinkers) to imagine that they are lying on the beach and for the last hour they have been thinking about how much they would enjoy a cold bottle of beer. A friend, then, offers them to bring back a beer from the closest place (a fancy resort hotel or, alternatively, a small grocery store) and asks how much they would be willing to pay for the beer. The friend, however, indicates that if the beer costs more than the price suggested, he would not buy the beer. What price would the participants be willing to offer? The median responses when the closest place to buy the beer was the resort was \$2.65; though, when the place was the small store, it was \$1.50. If the consumption experience is the same in either case (i.e., the beer is the same and the atmosphere is the same), why would participants be willing to pay more for the beer from the resort? Given that the acquisition utilities are the same in both scenarios, the discrepancy is due to the difference in transaction utilities. The resort is expected to evoke a higher reference price than the small store and therefore its transaction utility, or the value of its deal, is higher.

Another aspect of mental accounting is related to the decision to close an account. Decision makers are assumed to be reluctant to close an account in red and realize the loss (disposition effect). Because closing an account at a loss is painful, Thaler (1990) predicts that investors will be unwilling to sell securities that have decrease in value. Odean (1998), in effect, provides strong empirical support for this prediction after analysing records for 10,000 accounts at a large discount brokerage house. He found that investors show strong preference for realizing their gains than their losses, a behaviour that is suboptimal as it leads to lower after-tax returns, and that appears to be unjustified by the desire to avoid the higher trading costs of low prices stocks, or by the wish to rebalance portfolios.

1.2.2 How Activities Are Assigned to Mental Accounts?

So far, I have described how mental account works in the context of individual transactions. But, mental accounts can be defined more broadly in terms of spending categories in which budgets constrain spending. This budgeting process serves as a spending self-control device and, importantly, simplifies the representation of the decision-making process whenever there are competing uses for the available funds.

Thaler (1999) draws attention to the importance of labelling. Consumers routinely label mental accounts at different levels. Expenditures, such as housing, education, food, etc., are, for instance, organized into budgets. Different wealth accounts are also established based on how tempting is for the consumer to spend the money assigned to the account. For instance, a current income account would contain the cash on hand (which is spend regularly), a long-term savings account would contain stocks, mutual funds and other assets. Accounts are also labelled based on the source of income, such as accounts for regular income or accounts for windfall income. The fact that accounts under any of these levels are not perfectly fungible can give rise to wide set of apparent irrational behaviour.

To mention some examples of mental accounting effects for windfalls, in a series of experiments conducted by Arkes et al. (1994), participants were divided in two groups: the first group were told that they would receive $5 to participate in the study, whereas the other group was surprised to receive $5 when they arrived at the experiment. Later, both groups were sent to a basketball game. Participants in the unexpected money group spent more money on the game than the other group's participants. In a field study, Milkman and Beshears (2009) show that customers of an online grocery store who were given a $10-off discount coupon spend more on groceries that they do not typically buy.

1.2.3 How Mental Accounting Affects Intertemporal Choices?

Let us now turn to how mental accounting might influence intertemporal choices. We are particularly interested on how mental accounting rules impact consumers' payment decisions. Experimental research has shown that decision makers display different financing preferences depending on the characteristics of the good acquired. In a seminal paper, Prelec and Loewenstein (1998) propose a double-entry mental accounting model that helps to elucidate several, apparently irrational, consumer choices for the timing of payments. Their model suggests that there are reciprocal interactions between the pleasure of consumption and the pain of paying. On each episode of consumption, the consumer's mental accounting registers two sets of entries: one set records the net utility resulting from consumption after subtracting the disutility derived from the expected payments; the other set registers the net disutility of payments after subtracting the utility of the expected consumption. It is the anticipated sequence of these set of entries, the net consumption utility and the net payment utility, the criteria that guide consumer's purchase and payment decisions.

The key element of the model is the assumption of prospective accounting: consumer's mental accounting is forward looking. When people decide whether to purchase a product or not (and, implicitly, how and when to pay for the product), they only consider the hedonic effects of the current and future episodes of consumption and the current and future episodes of payments. In other words, making payments toward future consumption is more pleasant than paying for goods already consumed; also, consumption that has been paid beforehand can be enjoyed as if it were free. A straightforward consequence of this assumption is that the pleasure derived from the consumption of a product depends on when the product is paid for. Likewise, the pain of paying for the product depends essentially on when the product is consumed.

Given that episodes of consumption and payment call mental accounts to mind and induce either pleasure or pain depending on whether the accounts are in the red or in the black (i.e., with net loss or with net gain) and given the desire to keep accounts in the black, the model predicts that people would have a strong preference for accelerating payments of goods whose utility declines quickly over time (non-durable goods).

In fact, Prelec and Loewenstein's experimental evidence often reveals that people expose some form of debt aversion and dislike the possibility of consuming an item before paying for it. The following example illustrates this point clearly. Two scenarios were described to 91 visitors to the Phipps Conservatory in Pittsburgh. In the first scenario, the visitors were asked to imagine they were planning a one-week vacation to the Caribbean, six months from now, that will cost $1,200. They could finance the vacation by either a six-monthly payment of $200 before the beginning of the vacation or a six-monthly payment of $200 after returning. In the second scenario, the visitors were asked to imagine that they were planning to purchase a clothes washer and dryer that will cost $1,200 and that they could finance it by either six monthly payments of $200 before the machine arrives or by six monthly payments beginning after it arrives. More than 60% of visitors preferred the earlier payments in the first scenario. However, 84% of them chose to postpone the payments in the second scenario. A series of similar experiments, both between and within subjects, confirmed that this reversal of preference between financing options is robust.

Why do people's payment preferences change? We will return to this example in more detail in Chapter 3 but for now consider that when the payment schedule for the vacation is shifted into the future, there is a large hedonic fall at the very end of the vacation since there are only payments to look forward to. On the contrary, there is little psychological cost to delaying the payments for the dryer, as the dryer delivers sufficient residual utility over its lifetime to offset the remaining payments.

Although we believe Prelec and Loewenstein's body of evidence is valuable, no field evidence has yet been reported to test the mental accounting prediction described above, until now. This is the main motivation of Chapter 3. In Chapter 3, using transaction data from a sample of 1.8 million credit card accounts, we provide, to our knowledge, the first field test of this prediction. Specifically, we test whether consumers will pay off expenditure on transient forms of consumption more quickly than expenditure on durables

Note that the use of credit card data introduces some challenges. The fact that credit card payments are often later than purchase events decouples in some way the purchase from the payment. The longer the temporal distant between the credit card payment and the purchase episodes, and the larger the variety of products acquired, the consumer could likely experience more difficulties to attribute the credit card balance to the different purchases (i.e., the assignment of debt to mental accounts becomes less clear to the individual). Along Chapter 3, we address this problem by using different samples of the data in which the relationship between spending and repayment vary. Our first sample includes only the first month of data for new credit card accounts and includes only months in which all the spending is in either durable purchases or non-durable purchases. This sample exhibits no prior history of spending or repayment behaviour and so consumers are expected to have less difficulties to recognize the spending type. This is, therefore, the cleanest sample for our analysis. Our second sample also restricts data to only the first month for new credit card accounts, but now includes months in which the account incurs in durable and non-durable spends. In subsequent samples, we include all months, not just the first month. In a large array of analysis and in all the samples tested, we found that repayment of debt incurred for non-durable goods is more likely than repayment of debt incurred for durable goods, in consistency with Prelec and Loewenstein's prediction.

To summarize, in Chapter 3 we provide the first field evidence that shows that debt incurred on consumables is more likely to be paid off rapidly than debt incurred on durables, evidence that we think underpins the pivotal role of mental accounting in intertemporal choices.

1.3 Information Avoidance Among Investors

The following section focusses on the economic analysis of information. Particularly, we want to understand how preference for information are delimited by hedonic concerns. Under standard economic theory, information is valuable because it enhances decision making, i.e., because it leads (potentially) to better decisions. Information is seen as a mean to reach certain end. However, abundant situations exist in which information that could improve decision making is avoided. A recent study by Golman et al. (2017) provides in-depth analysis on the core reasons of why people might avoid information, even when they are aware that costless information exists or even when it is costly to avoid obtaining information.

Golman et al. (2017) classify information avoidance in two categories. The first category highlights events that are driven by strategic considerations (and so remain consistent with standard economic theory). For instance, consider the case when a speaker decides not to view a video of himself delivering a previous talk in order to prevent a loss of confidence in his next talk. The second category emphasises information avoidance motivated by hedonic considerations, i.e., when the individual expects that news would induce bad feelings. We are interested in hedonically driven information avoidance since it can hardly be accommodated by the standard economic framework. In this category, a number of psychological mechanisms could induce information avoidance. To mention some of these, information could be avoided because of disappointment aversion, anxiety, regret aversion, optimism maintenance, attention effects, or dissonance avoidance.

For concreteness, here we examine information avoidance induced by attention effects, which occur when new information provokes a temporal boost in the attention devoted to beliefs about some reality and, consequently, amplify the effects of those beliefs on the individual's utility. We focus our discussion on Golman and Loewenstein's (2015, 2018) theoretical framework of preferences regarding information. Golman and Loewenstein provide a cohesive theory that can explain both, the avoidance of potential useful information and the acquisition of non-instrumental information, contrary to alternative psychological mechanisms (as those mentioned above) that can only account for some particular patterns of behaviour.

The authors document substantial evidence from laboratory and field research that suggests that people derive utility from their beliefs about information gaps (i.e., unknowns that they are aware of) and not only from material payoffs as assumed by the standard economic theory. When a person is aware of a question and is uncertain about the answer, an information gap opens. The person forms beliefs or judgements about the answer to the question. These beliefs attract attention while the person continues to reflect upon the question and, hence, induce feelings that enter into the person's utility. To understand the situations in which people might avoid information, the authors propose a model of information acquisition and avoidance in which the individuals' utility function is defined over beliefs and the attention paid to them, and not only over objective outcomes.

Briefly, in Golman and Loewenstein (2015) model, a person's state of awareness is represented with a set of activated questions. A cognitive state is defined by the set of probabilities over the possible answers to these questions (and the prizes that could potentially be received). Attention weights define how much the person is reflecting about each activated question. Thus, these attention weights show how much the beliefs about each question impact the person's utility. To accommodate the cases in which individuals might seek answers to questions for their own sake, even when these answers have no use, the model assume that (holding attention fixed) there is a gain in utility from updating beliefs. Note that in their framework the utility function is defined over cognitive states. So a choice to acquire information is, essentially, a choice to accept a lottery over cognitive states (since, ex ante, the incoming information is unknown).

Based on an expected utility representation over cognitive states, the utility of acquiring information can be thought as the difference between the expected utility after receiving the information and the utility before receiving it. New information acquired could have the following consequences: it may change the value of future actions (and thus, inform future decisions), it may update the probabilities related to the answers to the activated questions (that is, it may increase knowledge about the correct answers), and it may change the attention weights, amplifying the value of the new set of beliefs and, therefore, intensifying their effect over the individual's utility.

These consequences shed light on three distinct motives for the demand for information. First, as in the standard economic framework, new information allows the individual to make better subsequent decisions, it has an instrumental value. Second, individuals are assumed to have a natural disposition to fill information gaps—i.e., to have innate curiosity. However, their degree of curiosity fluctuates. It is stronger about questions that are either more important or more salient. It is also stronger when the incoming information has the potential to fill multiple information gaps at once. Third, any new information is surprising and, thus, increases attention weights. The surprise reflects how much existing beliefs have changed. It is greatest if the individual has learned the most unexpected answer. With greater attention, there is a magnifying effect of the new information (new beliefs) on the individual's utility. However, the feeling of surprise is only temporal since the individual adapts to the new state of beliefs. It is because of this potential, although only temporal, hedonic effect of new information, that the individual might seek answers to questions he likes thinking about, questions in which answers might likely have positive valances.

The availability of information induces, therefore, two conflicting reactions. While innate curiosity can only encourage the acquisition of new information, the individual might refuse this new information in order to avoid increase his attention over negative beliefs. Thus, a straightforward prediction of Golman and Loewenstein (2015) framework is a desire for information regarding neutral or positive beliefs and a desire against information regarding negative beliefs if the bad feelings induced by these beliefs outweigh the pleasing effects of satiating curiosity.

There have been several investigations showing evidence consistent with Golman and Loewenstein's framework. For instance, Falk and Zimmermann (2016) conducted a laboratory experiment in which a lottery determined whether participants would receive a series of electric shocks. Participants could choose how they wanted to receive the information about the lottery outcome, either sooner or later. Before deciding, participants replied a brief multiple-choice quiz task. In one condition, after familiarizing with the task and before choosing how to be informed, participants were told that they would continue responding the task and that they would even be paid for their performance. In the control condition, no distracting activity was offered to participants and so they had to sit in front of the computer displaying the shocking device. Consistent with Golman and Loewenstein's model, when the prospect of receiving electric shocks was salient (because of the absence of a distracting activity), participants were about 30 percentage points more likely to request the information sooner.

In the financial literature, some prominent examples are the studies conducted by Karlsson et al. (2009). The authors provide evidence for ostrich-like behaviour in a finance context: an investors' inclination to avoid exposing themselves—sticking their heads in the sand—to information that might cause them psychological discomfort. Specifically, using two two-year period datasets from the Swedish Premium Pension Authority and the Vanguard Group in the US, that recorded investors logins to their personal portfolio accounts, they found that investors account monitoring choices were asymmetric: when the aggregate stock market was up, investors monitored their portfolio more actively than when it was down. However, later evidence provided by Gherzi et al. (2014) that covered the portfolio monitoring activity of a small sample of 617 clients from Barclays Wealth & Investment Management, over a 6-year period, showed that individual investors act more like hyper-vigilant meerkats than like head-in-the-sand ostriches. That is, investors increase their attention allocation not just after positive market returns but also after negative market returns, a pattern that apparently persist for daily non-trade logins and for weekend logins (when markets are closed) and that is moderated by the investors' degree of neuroticism.

Nevertheless, in a more recent study, Sicherman et al. (2015) investigated investors' patterns in aggregate attention and trading using a larger data of daily investor login activity than that use by Gherzi et al. (2014). Their panel data covered 1,168,309 investors with defined-contribution retirement accounts for the period 2007–2008. They identified ostrich-like login activity operating at daily, weekly, and monthly return horizons. They also identified that the ostrich effect is lager for males, wealthier investors, and investors who hold more equities than bonds. Their results also suggest that ostricity is a stable personality trait over time.

The above evidence serves as the starting point of the central ideas of Chapter 4. Although all these research efforts have provided us with valuable evidence, due to the scarcity of individual portfolio data, all of them were limited to the analysis of investors' attention at the aggregate level. As such, these studies have been mostly confined to explore only correlations between login activity and some proxies of the investor expectations about their portfolio returns, such as the VIX index, the Dow index and the FTSE100 index. Yet, when individual investors hold a few number of stocks only, as non-professional traders usually do, these indices (which cover typically hundreds of stocks) might hardly provide accurate information about their anticipated portfolio return movements. Furthermore, these studies are either short-term studies or small-sample-size studies, and so they do not capture the full story and cannot be used to generalize conclusions.

In Chapter 4, we are interested in how investors attribute selective attention to their portfolios. First, we examine the demand side for attention and explore whether investors' beliefs about their future portfolio returns have hedonic utility consequences. More precisely, we inspect whether investors regulate the impact of these beliefs on their utility by deliberately reducing their attention to negative beliefs (i.e., by avoiding bad news), as Golman and Loewenstein (2015) predict. Second, we examine the supply side for attention and evaluate how changes in the opportunity cost of attention affect investors' login activity. We look at exogenous shocks induced by weather changes that impact on the opportunity cost of attention.

We assembled and exploited a rich panel dataset containing anonymous account level records provided by Barclays Stockbroking. The data are sourced from Barclays' online execution-only brokerage platform and it covers the login and trading activity of a total of 155,309 accounts for a four-year period starting form 2012. The data contains information on investor characteristics, account logins by day and very detailed records of account activity and positions. All account activity is recorded in the data, including buy and sell trades, stock-splits and account management fees and charges. Given the richness of this account activity data, we were able to reconstruct individual account portfolios on any day of the data period, which allowed us to measure, among other things, how frequently clients log in to the online platform, how is their login activity around buy days, how their portfolio returns fluctuates in days with high login activity, and whether they are consistently attentive throughout the sample period.

Our findings in Chapter 4 are consistent with the notion that investors' account monitoring decisions have hedonic value. Attention appears to amplify the hedonic impact of information and, as such, investors make attention decisions in order to regulate their exposure to positive and negative information. Our findings also suggest that attention is susceptible to its opportunity cost. For instance, when the weather is good, and the opportunity cost is high (because investors could be enjoying the sun instead) investors choose to log in less often.

1.4 Plan of Thesis

Chapter 2 presents two field studies on police ethics. The first study evaluates peer effects in police ethical behaviour. It intends to answer the question of whether bad cops spread misconduct. We examine five years of allegations of misconduct recorded by the UK Metropolitan Police Service for nearly fifty thousand police offices. By using instrumental variable techniques and exploiting the variation in peer quality that results when officers change line managers and switch peer groups, we offer the first clear evidence of nontrivial peer effects in this domain. After examining the effect of corrupting colleagues in police misconduct, the second study investigates how responsive are police officers to the threat of discipline for their inappropriate behaviour. Our evidence suggests that only severe formal sanctions have some deterrent effect.

Chapter 3 is devoted to test a major prediction of Prelec and Loewenstein's (1998) double-entry mental accounting model. Specifically, we test whether consumers will pay off expenditure on transient forms of consumption more quickly than expenditure on durables. Using transaction data from a sample of 1.8 million credit card accounts, we provide the first field test of this prediction.

In Chapter 4, we move to a different domain and analyse how investors attribute selective attention to their portfolios. Using rich data provided by Barclays Stockbroking that recorded all account activity, such as buy and sell trades, stock-splits and account management fees and charges, and that enable us to reconstruct individual account portfolios, we show that investors account monitoring decisions have hedonic value and, as such, investors make attention decisions in order to mitigate (increase) their exposure to negative (positive) information. Then, Chapter 5 summarizes results from Chapters 2 to 4 and concludes this thesis.

Chapter 2

Bad Cop, Bad Cops: Learning and Peer Effects on Police Misconduct

2.1 Introduction

There is a growing body of literature that recognises the need for understanding the conditions that lead to police misconduct, since such incidents foster civilian distrust and hinder police work (Goldsmith, 2005). Research has revealed, for instance, that crime prevention cannot be pursued in the absence of public collaboration (policing by consent, Murphy et al., 2008). Moreover, actions perceived as unfair or arbitrary can affect police legitimacy, increase public suspicion, and even encourage retaliation (Bayley, 2002; Walker, 2006). Understanding the antecedents of misconduct will help develop interventions that reduce misconduct. We exploit a new dataset from London's Metropolitan Police Service which positions officers within their social network and follows them over time. We estimate how officers are affected by their own previous cases of misconduct and how officers are affected by the misconduct cases of their peers. Our estimation of these learning and peer effects complements the existing literature, in which there is much work on the how individual deviances predict misconduct and how organizational, social, and situational factors affect misconduct.

The individual deviance approach is appealing because of the long-established fact that the majority of incidents of corruption, brutality or excessive use of force are accounted by a handful of officers or "rotten apples". For example, in the US, the Christopher Commission that investigated the Los Angeles Police Department found that, over the period 1987 to 1991, 5% of the officers (of nearly 6000) were responsible for 20% of all reports of excessive use of force (Christopher, 1991). In the UK, in 1997 the then Commissioner of the Metropolitan Police Service Sir Paul Condon famously stated that there were up to 100-250 seriously corrupt officers in the Service (then, of about 27,000 officers; Gillard and Flynn, 2012; UK Government Select Committee on Home Affairs, 1997). That a few officers are responsible for much of the misconduct raises two possibilities: First, identifying and removing, or otherwise preventing, misconduct from this small number of officers would have a large effect. Second, and more worryingly, in the presence of strong peer effects, when the bad apples are not identified and disciplined, corruption can become pervasive and organized.

Research focused on the individual deviance approach shows that complaint-prone officers are more likely to be non-white (Harris, 2010; Kane and White, 2009; Lersch and Mieczkowski, 1996), male, less experienced (Brandl et al., 2001; Harris, 2009; Lersch and Mieczkowski, 1996; McElvain and Kposowa, 2004) and less educated (Kane and White, 2009; Kappeler et al., 1992). Recent work has also sought to understand the relationship between personality and misconduct. Donner and Jennings (2014), for instance, have shown that low self-control is a key predictor of engagement in general misconduct, particularly related to physical and verbal abuse. In the same vein, Pogarsky and Piquero (2004) found that impulsivity mediates the influence of legal and extra-legal sanctions on the decision to commit hypothesized acts of misconduct.

Since most officers will, at some point in time, have an allegation reported, more recent contributions have been driving the research towards the study of the likelihood and timing of the onset of misconduct. Harris and Worden (2014) investigated 938 officers of a police department in the north-eastern USA from the start of their careers and found that citizen complaints are likely to onset sooner than internal complaints, black officers had earlier onset, and prior military service appears to delay the onset. Interestingly, neither education nor academy performance had an effect on the timing of onset.

In contrast to the individual deviance view, research on organizational correlates of police misconduct is sparse. Some case studies have documented evidence of the influence of the police departments' characteristics, such as size, bureaucracy and professionalism on the decision to arrest (for a review see Dunham and Alpert, 2015). More recent evidence has shown that officers who perceive fairness in managerial practices are less likely to justify noble-cause corruption or adhere to the code of silence that protects bad cops (Wolfe and Piquero, 2011). Some consideration has also been given to situational variables. For instance, Hassell and Archbold (2010) found that having another officer on the scene at encounters that resulted in formal complaints does reduce the likelihood of these complaints being sustained, but has no apparent effect on the frequency of complaints. Also, the possibility of arrest at police-citizen encounters escalates with the mere presence of supervisors (Engel, 2000, 2003) and officers use greater levels of force against suspects encountered in high-crime and disadvantaged neighbourhoods (Terrill and Reisig, 2003).

The understanding of deviance behaviour should not neglect social aspects. People making decisions inside organizations are constrained to authority rules and regulations, but are also constrained to social norms, cultural expectations, and considerable large peer-group pressures. Kohlberg's research on moral reasoning (1969) has shown that, unlike childhood (when children were more concerned about the physical consequences of their actions, i.e., punishments and rewards, and when elements of reciprocity and fairness started to be incorporated pragmatically), moral reasoning in adolescence and adulthood is typically determined by beliefs about what others will think is right or wrong. In this level of moral thinking (termed as 'conventional' by the author), the individuals try to conform to the natural or accepted behaviour.

Compelling evidence for the existence of peer effects has already been documented in other settings. For example, Mas and Moretti (2009) found that the productivity of cashiers in a supermarket chain increases with the effort of co-workers who face them, Zimmerman (2003) demonstrated that first-year college students in the middle of the SAT distribution who share a room with students in the bottom of the distribution do worse in grades, and Trogdon et al. (2008) provided evidence that weight gain spreads through peer networks. The misconduct literature already suggests an association but the evidence of peer effects on officers' misconduct falls short of supporting a causal link. For example, officers assigned to the same workgroup tend to share occupational attitudes due to their interactions and exposure to similar environments (Ingram et al., 2013). This shows correlation in attitudes, but not a causal link. In the Philadelphia Police Department, officers who thought that their peers considered the use of excessive force as less serious were more likely to have citizen complaints, as were officers who anticipated more minor punishment for theft (Chappell and Piquero, 2004). Using the officers' judgments of their peers' attitudes, rather than objective measures of the actual attitudes of peers, allows only a correlational but not a causal claim. In the Dallas Police Department, one quarter of the variation in trainees' subsequent allegations of misconduct was attributed to field training officers in a multilevel analysis nesting trainees with their field training officers (Getty et al., 2014). Nevertheless, this multilevel analysis is likely to be driven by common variance elements that are typical in nested structures and thus do not reflect causal relationships.

Because evidence on peer effects in police misconduct remains speculative and largely restricted to cross-sectional studies, the first issue we address in this chapter is whether an officer's risk of misconduct increases when they are exposed to peer misconduct. That is, we aim to quantify the extent to which a bad apple would spoil the whole bunch. Estimating social learning is challenging as individuals from a peer group affect their peer group as much as the peer group affects them. In addition to this reflection problem, peer groups are not necessarily randomly sorted, as high-performance workers could be allocated to a high-performance peer group, and so workers from the same peer group might likely share common unobserved characteristics. Moreover, members of a group might show similar misconduct because they are subject to similar shocks (Manski, 1993). In our econometric approach, we address these issues using instrumental variable estimation techniques. We exploit the variation in peer quality that results after workers change line managers and switch peer groups. Misconduct of the new peers acquired following the change is instrumented with prior events of misconduct of their new peers' peers, allowing us to estimate the causal effect between peers. To pre-empt our results, being assigned to complaint prone peers increases the likelihood of misconduct events.

We should note that by examining peer effects, we do not intent to engage in the debate of what specific mechanisms are driving these effects. Nor do our data allow us to distinguish between the mechanisms by which peer effects are mediated. For example, we will not discriminate between social influences motivated by learning about what behaviour is best to follow given the individuals' own needs or motivated by pure peer pressure and social conformity. In fact, due to the difficulty to discriminate between these mechanisms, most research in the peer effects literature have focused on measuring the magnitude of peer effects only and have overlooked the mechanisms that may be generating the peer effects.

After examining the effect of corrupting colleagues in police, the second issue we address is whether officers learn from their previous cases of misconduct and whether sanctions help to dissuade misconduct. Learning from errors is vital in many psychological domains (like education, Metcalfe, 2017), and the role of reward and punishment is key (O'doherty et al., 2017). Moreover, existing research on deterrence recognizes that both the perceived risk of being sanctioned and the sanctions' severity lowers the recurrence of illegal activity (Nagin, 1998). Unfortunately, the literature on police misconduct fails to clarify whether past exposure to allegations of misconduct or complaints reduces the probability of future misconduct, and whether past sanctions or punishment mediate learning.

The evidence of the deterrent effect of the sanction threats for police misconduct is counterintuitive and largely speculative at present. For instance, in a survey about police misconduct conducted by Pogarsky and Piquero (2004) of police officers from a southwestern USA police department, it was found that the perceived sanction severity had little deterrent threat on subsequent misconduct. Only perceived sanction certainty and perceived sanction celerity were negatively connected with police misconduct. However, extra-legal sanctions, such as social disapproval, shame or embarrassment, were found to be a major deterrent against police misconduct. More counterintuitively, Harris and Worden (2014) examined personnel complaints against 1,356 patrol officers from a police department in the northeaster USA and identified that officers who received more severe sanctions were more likely to receive an additional sustained complaint when compared with no sanctioned officers. The authors hypothesized three reasons for their results: punishment could be an indicator of the most active offenders who are less likely to be deterred; those punished mistakenly believe that the punishment experience prevents them from future apprehension on the next offenses (since sanctions are relatively rare, they reset their sanction certainty, as in the gambler's fallacy); or those punished might perceive the sanctions as unfair, which ultimately prompts them to defy and increase offending. Although the authors could not discriminate among these alternative reasons, they speculate that the most plausible explanation is the perceived injustice of the disciplinary system that may encourage officer deviance. They argue that officers, even those largely bonded to the peer group, tend to be distrustful of their police departments.

Since the above findings are controversial and since police disciplinary systems are substantiated on the notion of deterrence, in the second part of this study we estimate the extent to which receiving allegations of misconduct diminishes the likelihood of subsequent misconduct and, crucially, we also estimate whether disciplinary actions resulting from earlier misconduct allegations mediate this effect. To pre-empt our results, repeated exposure to allegations that led to formal disciplinary actions leads to subsequent declines in misconduct.

Note that a strength of our panel dataset is that we can identify employees and their different peers and supervisors over time, enabling us to control for unobserved individual heterogeneity and limiting the risk that our results reflect spurious rather than authentic relationships. Therefore, unlike previous research that analysed the effect of sanctions on the likelihood and timing of complaints filed against officers ignoring (or incorrectly accounting for) individual heterogeneity, we test the deterrent effect of the sanction threats via a dynamic model that takes into account any individual (time invariant) difference among officers. Our results show that standard models that ignore individual heterogeneity are largely flawed as they ignore the fact that severe sanctions could simply correlate with future misconduct episodes for the most complaint-prone officers.

This chapter unfolds as follows: First, we describe the complaints data. Then, we present the details of the econometric methodology for the analysis of peer effects and report our findings on peer effects together with some falsification tests. Next, we present the details of the econometric methodology used to estimate learning effects from previous experience of allegations and report our findings on learning. Finally, we discuss our results and close.

2.2 Data Sources

Our study uses four databases maintained by the Metropolitan Police Service. The first dataset contains demographic information for 13,558 civilian staff and 35,845 police officers in active service at the end of the first quarter of 2015. The second dataset includes daily records of allegations of misconduct filled against civilian staff and police officers from the second quarter of 2010 to the first quarter of 2015. Each record contains fields for the date of the incident, the nature of the allegations and the complaint's final disposition (if any). Allegations include citizen complaints and internal complaints filled by supervisors or other officers, however the records do not distinguish between these two sources. The third dataset comprises the individuals' performance scores reported on annual basis in Performance Development Reviews from 2011 to 2014. Scores are given on specific categories: operational effectiveness, organizational influence, resource management, and final overall rating of performance. The fourth dataset contains semestral records of employees and their line managers from 2011 to 2015. The final panel of data, obtained by merging these data sources, has repeated quarterly observations nested within each of the individuals. It compromises 47,991 people (28.2% were civil staff; 65.1%, males; and 11.2%, from black and minority ethnic groups) for the period 2011 to 2014. In this final panel of data, we were able to identify the workgroups for 35,924 individuals by linking officers assigned to the same supervisor in a given quarter.

2.3 Descriptive Statistics for Complaints

During the second quarter of 2010 to the first quarter of 2015, 19,251 people had cases of complaints. However, as Figure 2.1 shows, most of them (74.7%) receive only 2 or fewer complaints in this five-year interval. Note that this is a very common pattern in police departments (Dunham & Alpert, 2015), suggesting that misconduct is not systemic and apparently only a minority of officers (or roles) are complaint-prone.

Allegations of misconduct are classified in six categories: failures in duty, malpractice, discriminatory behaviour, oppressive behaviour, incivility, traffic, and other allegations. Their distributions in Table 2.1 reveals that for both members of police staff and for police officers, the most recurrent allegations consist of cases of failures in duty, which can be, for instance, unjustified use of the relevant power, unauthorised entry on search, failure to inform detained persons of their rights and entitlements, failure to maintain proper custody/property records, interviewing oppressively or in inappropriate circumstances, among other cases.

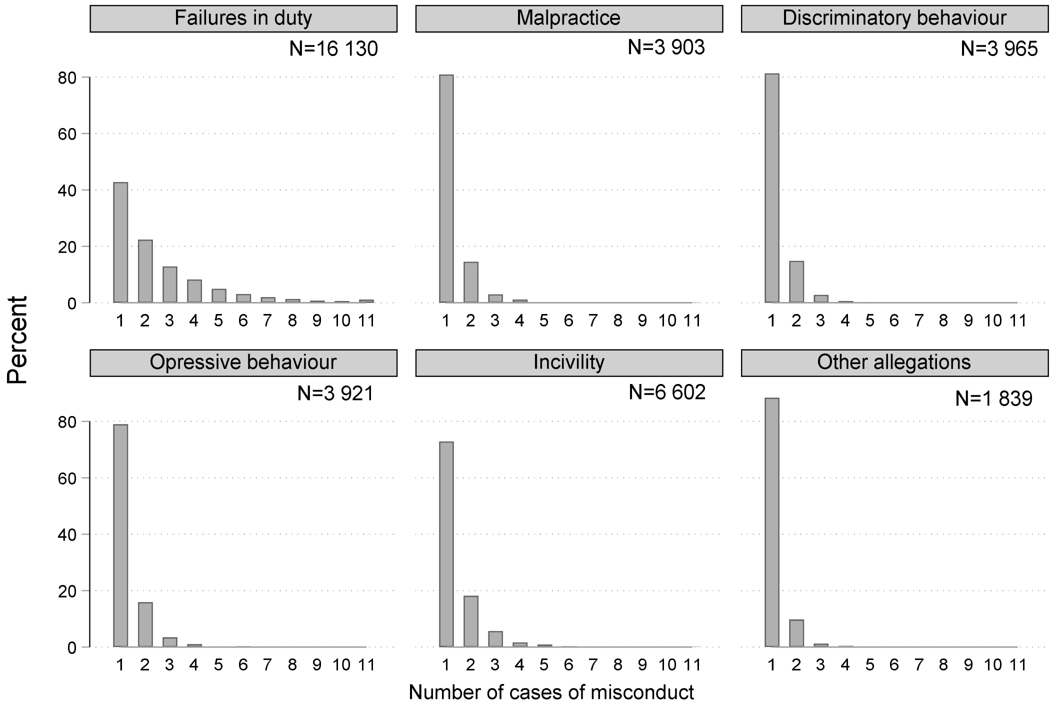


Fig. 2.1 The distribution of individuals according to the number and type of misconduct received over the period 2010Q2-2015Q1. Other allegations include traffic allegations. The cohort included 19,251 people.

Table 2.1 The Distribution of Allegations Against Civil Staff and Police Officers by Disciplinary Outcome

	Action Type											
	Civilian Staff						Police					
Allegation Type	No Action	Management Action	Formal Action	Unsatisfactory Performance Procedure (UPP)	Retired / Resigned	Total	No Action	Management Action	Formal Action	Unsatisfactory Performance Procedure (UPP)	Retired / Resigned	Total
Failures in duty	1,366 (53.74%)	651 (25.61%)	522 (20.54%)	2 (0.08%)	1 (0.04%)	2,542	31,075 (86.43%)	3,924 (10.91%)	873 (2.43%)	79 (0.22%)	1 (0.00%)	35,952
Malpractice	82 (47.13%)	21 (12.07%)	70 (40.23%)	0 (0.00%)	1 (0.57%)	174	3,638 (88.95%)	345 (8.44%)	96 (2.35%)	9 (0.22%)	2 (0.05%)	4,090
Discriminatory behaviour	139 (72.40%)	43 (22.40%)	10 (5.21%)	0 (0.00%)	0 (0.00%)	192	4030 (91.95%)	289 (6.59%)	59 (1.35%)	5 (0.11%)	0 (0.00%)	4,383
Oppressive behaviour	47 (83.93%)	7 (12.50%)	2 (3.57%)	0 (0.00%)	0 (0.00%)	56	4,143 (92.56%)	295 (6.59%)	30 (0.67%)	8 (0.18%)	0 (0.00%)	4,476
Incivility	529 (47.36%)	515 (46.11%)	71 (6.36%)	1 (0.09%)	1 (0.09%)	1,117	6,832 (85.41%)	1,027 (12.84%)	135 (1.69%)	4 (0.05%)	1 (0.01%)	7,999
Traffic	22 (28.95%)	15 (19.74%)	39 (51.32%)	0 (0.00%)	0 (0.00%)	76	382 (67.61%)	135 (23.89%)	46 (8.14%)	2 (0.35%)	0 (0.00%)	565
Other	98 (34.39%)	43 (15.09%)	144 (50.53%)	0 (0.00%)	0 (0.00%)	285	818 (80.91%)	130 (12.86%)	63 (6.23%)	0 (0.00%)	0 (0.00%)	1011
Total	2,283 (51.40%)	1,295 (29.15%)	858 (19.32%)	3 (0.07%)	3 (0.07%)	4,442	50,918 (87.08%)	6,145 (10.51%)	1,302 (2.23%)	107 (0.18%)	4 (0.01%)	58,476

Note. Allegations recorder against 2,526 civil staff and 16, 725 police officer over the period 2010Q2 to 2015Q1. Other allegations include traffic allegations. Most formal actions (87.55%) were taken based on substantiated allegations, while only 3.27% management actions and 0.04% no actions were linked to substantiated allegations.

The possible sanctions following misconduct are formal actions, unsatisfactory performance procedures (UPPs), management actions, retirement or resignation, though most complaints end in no sanction. Formal actions involve written warnings, while UPP entails the organizational procedures designed to deal with unsatisfactory performance and attendance. Management actions refer to any action that can be locally resolved to handle the allegation of misconduct. They consist of, for example, the establishment of an improvement plan and the clarification of expectations for future conduct. Observe in Table 2.1 that very few cases received a formal disciplinary action. Furthermore, over 50% of allegations against members of police staff and about 90% of the allegations against police officers had no subsequent actions taken. Most of these allegations were instances in which, following investigation and based upon the available evidence, there was no case to answer concerning the allegation. It can then be argued that the allegations documented might over represent real events of misconduct. Nonetheless, research has shown that allegations are difficult to prove because of the relative lack of physical evidence and the absence of witnesses and, thus, cases deemed unsubstantiated do not necessarily imply the absence of police misconduct (Harris and Worden, 2014; Prenzler and Ransley, 2002). Note that the use of all allegations, irrespectively of their outcomes, is the usual approach adopted in the literature.

Table 2.2 shows how the types of allegations correlate within individuals. People with alleged failures in duty seem to also exhibit, to some extent, some form of incivility and oppressive or discriminatory behaviour.

2.4 Analysis of Peer Effects

2.4.1 Econometric Model

Our first analysis explores whether workers' peers' misconduct might affect the recurrence of workers' misconduct events. Peer groups were defined by linking officers and staff assigned to the same line manager. For analysis we required line manager history (from which we can infer peer groups), at least one peer, and demographic information. This was true for 35,924 officers and staff. Our outcome is a binary variable, y_{it}, that equals one if worker i had an event of misconduct during quarter t. Our independent variable of interest is the proportion of peers of i in $t-1$ receiving reports of misconduct in $t-1$.

Table 2.2 Correlation of Allegations Within Individuals

	Failures in duty	Malpractice	Discriminatory behaviour	Oppressive behaviour	Incivility
Malpractice	0.212 [0.198 - 0.225]	1.000			
Discriminatory behaviour	0.285 [0.272 - 0.297]	0.098 [0.084 - 0.112]	1.000		
Oppressive behaviour	0.302 [0.289 - 0.315]	0.147 [0.133 - 0.161]	0.168 [0.154 - 0.182]	1.000	
Incivility	0.316 [0.303 - 0.329]	0.066 [0.052 - 0.080]	0.241 [0.228 - 0.254]	0.145 [0.131 - 0.158]	1.000
Other	0.080 [0.066 - 0.094]	0.040 [0.026 - 0.054]	0.038 [0.024 - 0.052]	0.041 [0.027 - 0.055]	0.078 [0.064 - 0.092]

Note. Pearson correlations of allegation types within individuals with 95% confidence intervals in brackets. Other allegations include traffic allegations.

Since officers who patrol together or are in certain units together have a higher likelihood of being involved in reports of misconduct that might not be their fault, to prevent overestimating the effects of peers' misconduct, we consider as events of peer misconduct only those episodes in which i had no same-day concurrent allegations of misconduct. That is, allegations against peers and allegations against the target officer i correspond to different cases and were reported on different dates. W is a vector of control variables that include demographic characteristics, such as gender, length of service, employee's business group, employee type, and employee performance; and additional controls for annual and seasonal effects.

$$y_{it} = 1[\rho Peer\ y_{i,t-1} + \sum_f \phi_f W_{fit} + \varepsilon_{it}] \tag{2.1}$$

Empirically there are three challenges for the identification of peer effects (Angrist, 2014; Manski, 1993). First, due to non-random assignment into groups, individuals with similar characteristics may end up in the same group. Then what looks like peer effects could actually be due to common characteristics of the individuals themselves and not due to their peers. Without random assignment, the influence of individual's characteristics cannot be identified separately from the influence of their peer's characteristics. The second challenge is that, even when random assignment had been possible, individuals in the same group share similar environments and, thus, there could be unobservable institutional factors affecting the group members' performance simultaneously. These two threats are referred to in the literature as correlated effects and do not correspond to any social phenomenon between peers. Third, we would expect peer effects to be bi-directional. This means that peer effects are, in part, a property of the target individual and are not exogenous to the individual. This reverse causality problem holds even if we had random assignment into groups.

To address these challenges, we proceed as follows. To absorb the effect of unobservable institutional factors affecting the likelihood to misbehave either because some workers are exposed to particular stressful environments or high crime areas, or because workers sharing some background characteristics preferred to join specific business groups, our econometric specification includes dummy variable controls for the business groups the employees belong to. These business groups include: Territorial Police (divided in Boroughs North, Boroughs South, Boroughs West, Central, Criminal Justice & Crime, and Westminster), Specialist Crime and Operations, Specialist Operations, and Other Business Group (which aggregate the groups Career Transition, Deputy Commissioners Portfolio, Directorate of Resources, Met HQ, National Functions and Shared Support Services). Our regressions also include quarter and year dummies to account for any seasonal fluctuation in crime.

To deal with individual heterogeneity, we also include controls for gender, years of length of service, employee type and police ranks, and police performance. Performance scores are reported on an annual basis in Performance Development Reviews and evaluate competencies in operational effectiveness, organizational influence, and resource management. To alleviate the concerns of simultaneity bias, note that we estimate the effect of lagged peer outcomes on misconduct. More importantly, to deal with endogenous worker sorting into peer groups and potential correlated effects unaccounted by our set of controls, we use instrumental variable techniques and estimate a linear probability model using two-step Generalized Method of Moments (GMM) estimators. Our identification strategy exploits the variation in peers that is experienced by workers who switch peer groups.

Figure 2.2 illustrates the procedure followed. The top panel shows the hypothetical composition of peer groups for three different line managers across one year, from $t-3$ to t. We are interested in modelling the risk of misconduct of individual i (denoted as 'T', for target individual, from now on) at time t. 'T' is allocated to a new line manager, Line Manager 2, in quarter $t-1$ and encounters new peers, 'D', 'E', 'F', 'G', and 'H' workers. First, we look at his new peers and select those that were also recently allocated to Line Manager 2 (i.e., 'H'). Second, for the identified peer 'H', we observe his existing peers in $t-2$ ('I', 'J', and 'K') and compute the proportion of these existing peers who had reports of misconduct in $t-2$ (P1). Likewise, we also observe his existing peers in $t-3$ (again, 'I', 'J' and 'K') and compute the proportion of these existing peers who had reports of misconduct in $t-3$ (P2). These two measures are used as instruments of $Peer\ y_{i,t-1}$ in Equation 2.1. Note that the construction of our instruments ignores the behaviour of any worker that was under the supervision of Line Manager 2 during $t-2$ and $t-3$, such as workers 'D', 'E', 'F', and 'G', since due to potential non-random sorting these workers might share some background characteristics with 'T'.

Valid instruments satisfy two properties. The instrument must be (1) relevant: the instrument must be correlated strongly with the endogenous variable $Peer\ y_{i,t-1}$. The instrument must satisfy the (2) exclusion restriction: the instrument must affect the outcome variable, $y_{i,t}$, only through its effect on the endogenous variable. That is, the instrument should not affect independently the outcome variable $y_{i,t}$. The exclusion restriction implies that misconduct of the peers of 'H' in $t-2$ and $t-3$ (i.e., misconduct of 'I', 'J', and 'K') should not affect the current behaviour of 'T' except through their impact on 'H' in $t-1$. If 'H' had not been allocated to Line Manager 2, the behaviour of I', 'J', and 'K' should not affect the behaviour of the target officer 'T'. Accordingly, to construct our instruments we discard in the first part of our procedure any new peer of 'T' in $t-1$ that had at least one peer that worked along 'T' during quarters $t-3$ to t. This strategy satisfies the exclusion restriction since only the peers of peers who had no evidence of direct contact with 'T' during the past year are used in the construction of the instruments. Note that 'I', 'J' and 'K' satisfy this criterion.

In the bottom panel of Figure 2.2, we consider the case in which 'T' experiences new peers but does not change line manager. Following the same procedure, we select 'H' and observe the behaviour of his peers in $t-2$ and $t-3$ to construct the instruments. In our examples, only 'H' was selected in the first step; however, when more than one peer in $t-1$ satisfy the criteria imposed, we compute for each of these peers the two measures of peers of peers conduct described ($P1$ and $P2$) and average these measures across them. Thus, we use ($\bar{P}1$ and $\bar{P}2$) as instruments of $Peer\ y_{i,t-1}$.

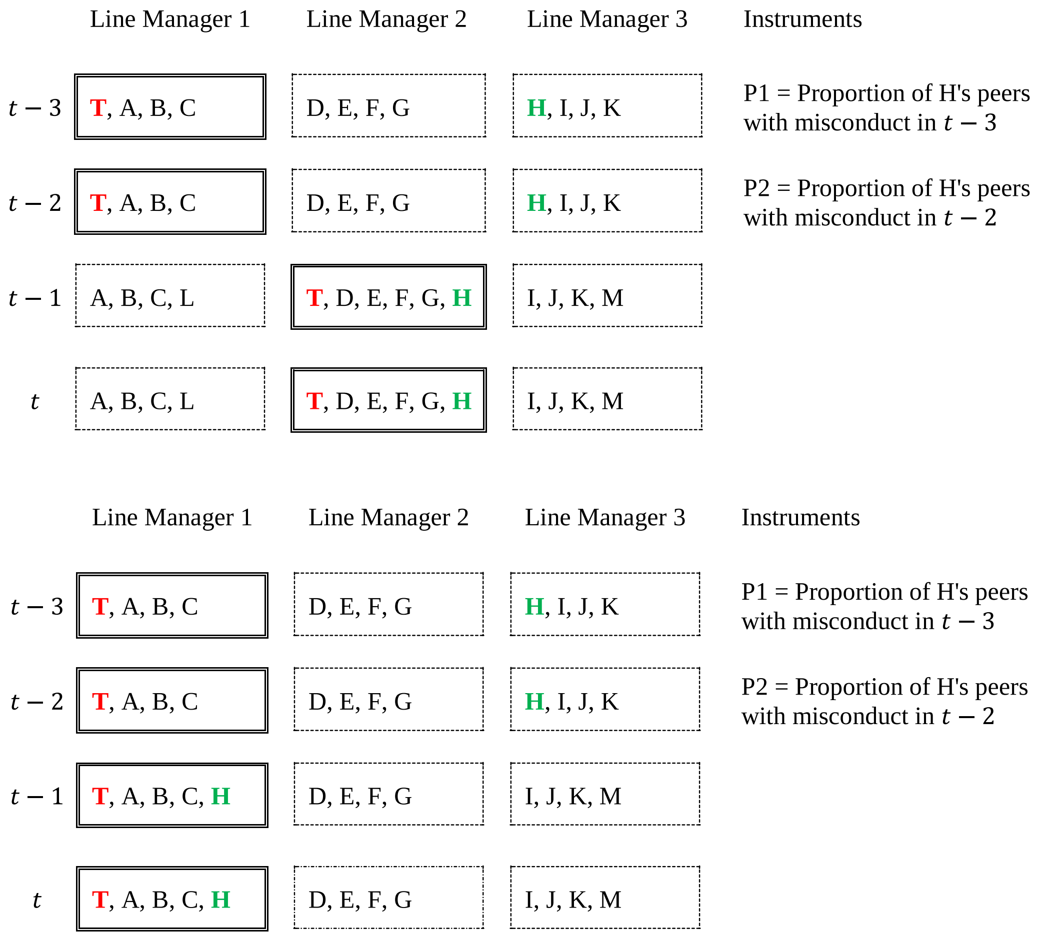


Fig. 2.2 The identification strategy for peer effects. Each column represents the peer groups under the direction of three different line managers over time. 'T' is the target individual under study. The double line frames highlight the groups that 'T' belongs to at each time. In time $t-1$, 'T' experiences a different peer group, either because he switches line manager (top panel) or because new workers are assigned to his group (bottom panel). In both cases, the behaviour of 'I', 'J', and 'K', who are the peers of worker 'H' in $t-2$ and $t-3$, are used as instruments of the peers of 'T' in $t-1$. Observe that 'I', 'J' and 'K' had no direct contact with 'T' during the past year (i.e., $t-3$ to t) and so this strategy satisfies the exclusion restriction required for identification.

Observations that satisfy our criteria for identification are not prevalent in the data and, thus, our estimation of peer effects is restricted to a sample of 80,632 quarter observations (25% of the total quarter observations of the data) from 30,627 individuals. A summary of the average composition (by quarter) of the sample used is shown in Table 2.3. The left column displays the average composition per quarter for the whole sample.The left column displays the average composition per quarter for the whole sample. The right column restricts the sample to those observations in which an individual faces a change of peers. Figure 2.3 shows the distribution of the number of peers for each of these samples. There is not apparent evidence of a disproportionate selection of particular groups of individuals, which means our estimates of peer effects should generalise to the wider population of all officers and civilian staff.

2.4.2 Results

We have outlined above how the instrumental variable estimation approach is critical to addressing the three challenges for identification of the causal effect of peer misconduct. To have an initial approximation of the direction and magnitude of peer effects on misconduct, in the Appendix A we present the estimates from linear probability panel data models—including both fixed and random effects—that cover all individuals in our data. These panel models do not correct for endogeneity. While these panel models can be applied to the whole data set, they do not address the three challenges to estimating the casual effect. We find that the panel models show significant but small effects of peer misconduct. But our instrumental variable approach reveals that the panel models greatly underestimate the causal effect of peer misconduct.

Table 2.4 presents the estimates using our instrumental variable approach. The first variable, the proportion of peers in $t-1$ with misconduct, is instrumented using the proportion of peers of 'H' with misconduct from Figure 2.2 (i.e., using the proportion of 'I', 'J', and 'K' with misconduct). In Model 1, we present the estimates from a two-step efficient GMM estimator (results from the first stage are presented in Table A.2.1 of Appendix). Due to the instrumenting of our endogenous variable, 75% of the observations are lost; however, as described earlier in Table 2.3, the remaining sample is structurally similar to the whole sample. Since in this remaining sample more than half of the individuals (15,038 out of 30,627) have only 2 or 3 quarter observations, we are unable to apply panel data estimators. However, the SEs of our GMM

Table 2.3 Composition of The Data Used to Estimate Peer Effects

	Whole sample	Individuals who experience new peers
Gender		
Male	0.65	0.68
Employee type		
Police Constable	0.54	0.61
Police Sergeant	0.12	0.13
Inspector	0.03	0.03
Chief Inspector, Superintendent, Chief Superintendent	0.01	0.01
Special Constabulary	0.00	0.00
Civil Staff	0.30	0.22
Business Group		
TP - Boroughs North	0.07	0.08
TP - Boroughs South	0.10	0.12
TP - Boroughs West	0.08	0.10
TP - Central	0.00	0.00
TP - Criminal Justice & Crime	0.12	0.11
TP - Westminster	0.03	0.03
Specialist Crime and Operations	0.27	0.26
Specialist Operations	0.12	0.11
Other Business Group	0.10	0.05
Length of service (years)	13.45	1.28
Exceptional + Competent (above standard)	0.49	0.49
Competent (at required standard)	0.50	0.51
Competent (development required) + Not Yet Competent	0.01	0.01
Events of misconduct		
Incidence of misconduct	0.05	0.06
Incidence of failures in duty	0.04	0.04
Incidence of malpractice	0.01	0.01
Incidence of discriminatory behavior	0.01	0.01
Incidence of oppressive behavior	0.01	0.01
Incidence of incivility	0.01	0.01
Occurrence of Formal disciplinary actions following misconduct	0.00	0.00
Occurrence of Management disciplinary actions following misconduct	0.01	0.01
Occurrence of No disciplinary actions following misconduct	0.04	0.04
Total number of quarter observations	331,023	80,632

Note. The table displays the composition of the whole data (left column) and the data used to estimate peer effects via instrumental variable regressions (right column).

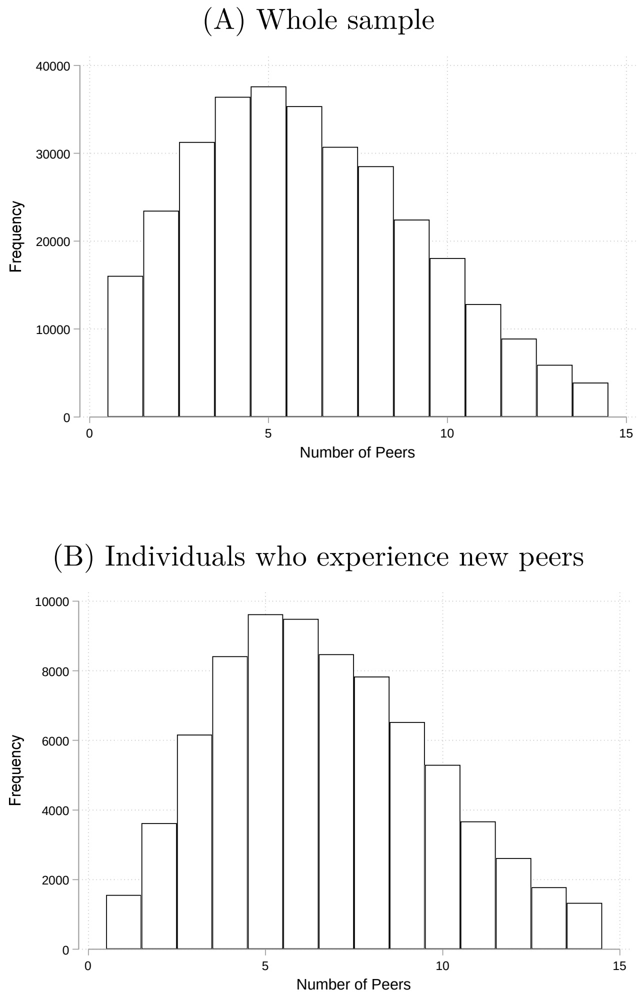


Fig. 2.3 Distribution of number of peers by sample. The top panel includes all quarters. The bottom panel restricts the data to those quarters that satisfy our criteria for identification. Outliers below the 5-percentile and above the 95-percentile of the distribution are excluded.

Table 2.4 The Estimated Likelihood of Misconduct, Peer Effects

	Individuals who experience new peers	
	(1)	(2)
VARIABLES	GMM	IVPROBIT
Prop. of peers in $t-1$ with misconduct	0.768***	5.426***
	(0.157)	(0.703)
Gender (reference: Females)		
Male	0.017***	0.140***
	(0.002)	(0.019)
Employee type (reference: Civil Staff)		
Police Constable	0.017***	0.210***
	(0.004)	(0.042)
Police Sergeant	0.022***	0.270***
	(0.005)	(0.047)
Inspector	0.019***	0.254***
	(0.006)	(0.056)
Chief Inspector, Superintendent, Chief Superintendent	0.016*	0.143
	(0.006)	(0.091)
Business Group (reference: TP - Boroughs East)		
TP - Boroughs North	-0.001	-0.005
	(0.004)	(0.027)
TP - Boroughs South	0.007	0.038
	(0.004)	(0.024)
TP - Boroughs West	0.002	0.013
	(0.004)	(0.026)
TP - Central	-0.033**	
	(0.012)	
TP - Criminal Justice & Crime	0.006	0.066*
	(0.005)	(0.028)
TP - Westminster	0.006	0.034
	(0.006)	(0.038)
Specialist Crime and Operations	-0.006	-0.053
	(0.005)	(0.038)
Specialist Operations	-0.013~	-0.163**
	(0.007)	(0.060)
Other Business Group	-0.001	-0.204**
	(0.007)	(0.076)
Length of service		
Length of service (10 years)	-0.013*	-0.057
	(0.006)	(0.048)
Length of service (10 years)^2	0.002	-0.003
	(0.002)	(0.013)
Employee Rating in $t-4$ (reference: Competent but development required + Not Yet Competent)		
Exceptional + Competent (above standard)	-0.038**	-0.285***
	(0.012)	(0.073)
Competent (at required standard)	-0.035**	-0.256***
	(0.012)	(0.069)
Constant	0.038*	-1.606***
	(0.018)	(0.075)
Observations	80,632	80,612
Number of individuals	30627	30617
LM test statistic for under identification (Kleibergen-Paap)	199.3	
P-value of under identification LM statistic	$p<0.001$	
F statistic for weak identification (Kleibergen-Paap)	97.75	
Hansen Statistic	0.520	
Degrees freedom of Hansen Statistic	1	
P value Hansen Statistic	0.471	
Wald test of endogeneity, $\chi^2(1)$		29.97
Exogeneity test Wald p-value		$p<0.001$
Quarter FEs	YES	YES
Year FEs	YES	YES

Note. All models estimate the probability of an event of misconduct in quarter t conditional on a set of covariates. The dependent variable is a dummy equal to one when at least one event of misconduct is reported in quarter t. The independent variable of interest is the proportion of peers in quarter $t-1$ with reported cases of misconduct. Our identification strategy exploits the variation in peer groups experienced by the individuals during the period 2011-2014. We use instrumental variable techniques for the identification of peer effects. Column 1 presents a 2-step GMM linear model and Column 2, an IV probit model. Two instruments are used for identification: the average proportion of peers of peers with incidence of misconduct in $t-2$ and, likewise, the average proportion of peers of peers with incidence of misconduct in $t-3$. The models include dummy controls to account for seasonal variation in the report of misconduct events: Quarter FE and year FE correspond to quarter dummies and year dummies. Standard errors clustered by individuals in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, p<0.10.

estimates are robust to arbitrary within-individual correlations. The coefficient of 0.768 for the instrumented proportion of peers at $t-1$ with misconduct means that a 10-percentage point change in the proportion of peers with misconduct would cause an increase of 7.68 percentage points in the target misconduct.

In Model 1, the estimates for the control variables are in line with the findings of other studies in the literature: male workers, police officers and less experienced employees are prone to receive more allegations of misconduct. We also see expected signs for a positive effect of previous employee performance reviews.

At the bottom of the Model-1 Column of Table 2.3, we test the validity of our instruments. To be valid, they should satisfy two requirements: they must be correlated with the endogenous variable $Peer\ y_{i,t-1}$ and orthogonal to the error process. At the bottom of Table 2.3, we report the first-stage Kleibergen-Paap F-statistics for week identification that examines the joint significance of the both instruments in determining the endogenous variable. With a value of 97.75, sufficiently larger than 10, the threshold suggested by Staiger and Stock (1997) to prevent biases by using weak instruments, the first-stage F-statistic confirms that our instruments are strong. We also report the Kleibergen-Paap LM test statistic for under identification which is robust in the presence of heteroscedasticity and clustering in errors. Rejection of the null indicates that our model is identified—that is, that our instruments are relevant. To evaluate the validity of the instruments, we also report the J-statistic of Hansen (1982) that tests the null hypothesis of orthogonality of the instruments and the error process which shows that our instruments are exogenous.

In Model 2, we use an alternative estimator, an instrumental variable probit estimator, which also alleviates endogeneity concerns, but it is appropriate for binary dependent variables and continuous endogenous covariates. The resulting estimates provide further statistical support for the presence of peer effects. At the bottom of the column for Model 2, we also report the χ^2 statistics of the Wald test of endogeneity of the instrumented variable, which rejects the null hypothesis that $Peer\ y_{i,t-1}$ is exogenous.

Coefficients from Model 2 do not represent marginal effects as coefficients from Model 1 do. In order to ease the comparison of both models, Figure 2.4 illustrates the extent of the peer effects from Model 2. Reassuringly, the peer effects are close in magnitude to those obtained by GMM in Model 1.

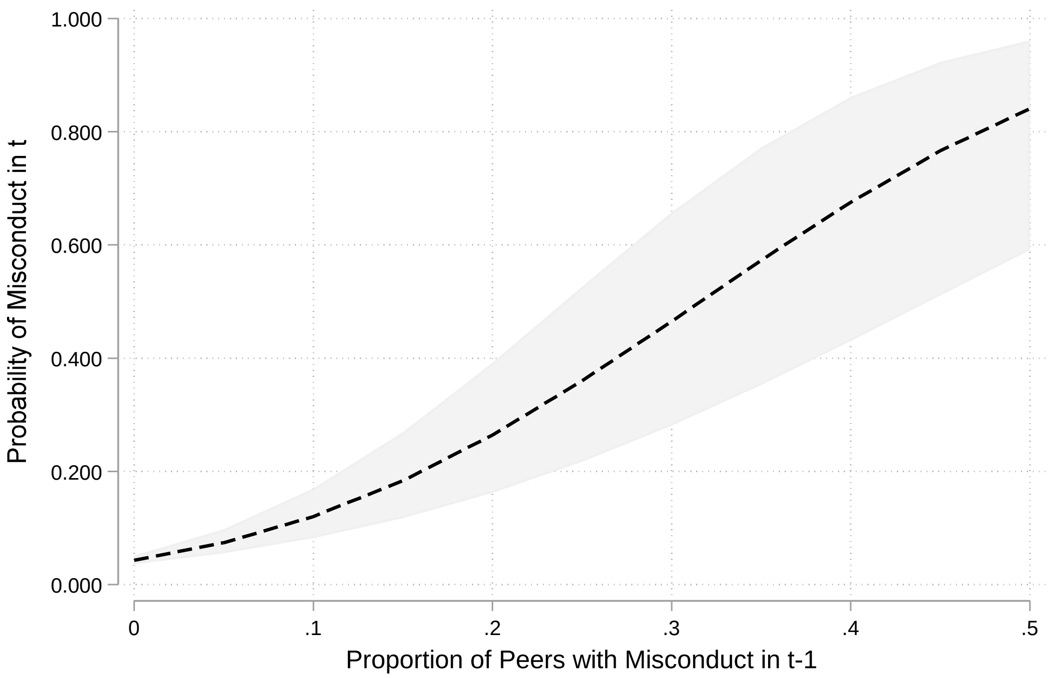


Fig. 2.4 Fitted probability of misconduct at t conditional on the proportion of peers exhibiting events of misconduct in $t-1$. The shaded area represents 95% confidence intervals. Peer effects are based on estimates of Model 2 of Table 2.4.

2.4.3 Falsification Tests

Under the concern that our estimation of peer effects might still reflect correlated effects due to unobservable events not accounted by our controls or endogeneity due to disregarded indirect interactions between individual i and the peers of peers used in the constructions of our instruments, we perform the following falsification test. Observe in the top panel of Figure 2.2 that the behaviours of individuals 'I', 'J' and 'K' are expected to influence the conduct of 'T' during quarter t through a single and unique channel, 'H'. However, during quarter t former peers of 'T' (i.e., 'A', 'B' and 'C') who remained under the direction of Line Manager 1 and, consequently, had no direct contact with 'H' should not be affected by any sort of misconduct of 'I', 'J' or 'K' that took place during quarter $t-2$ or $t-3$. Thus, our falsification test consists on replacing the dependent variable y_{it} by the proportion of former peers of i who receive allegations of misconduct during quarter t. These peers are those who worked along i during quarter $t-2$ (the period immediately preceding the movement of i into a new peer group). The control variables are analogous to those used in Table 2.4. They include the proportion of male peers, the proportions of peers for each rank, business group and performance rating, the average length of service and the usual year and seasonal controls.

Models 1–3 of Table 2.5 present the results of this falsification test. Models 1–3 are fitting the misconduct of former peers of the target, who should be unaffected by our instrument. The sample size for our falsification test is smaller because it is restricted to those quarter observations in which individuals change line managers (illustrated in the top panel of Figure 2.2). Model 4 of Table 2.5 is fitting misconduct of the target, and here we should replicate our headline peer effect from Model 5 of Table 2.4, but on the smaller sample size.

The peer effects for Models 1–3 of Table 2.5 are much lower, imprecise, and not statistically different from zero, as we expected from the falsification test. Model 4 of Table 2.5 produced estimates very like those found in Table 2.4 Model 5, replicating our headline peer effect within the smaller sample. The specification tests confirm the validity of the instruments in all models, as informed by the Hansen J-statistics and F-statistics, except for Model 3. Yet, any possible endogeneity problem that remains unsolved in Models 1–3 would induce some upward bias in the estimated peer effects these columns display. However, these peer effects are of small and non-significant size. Regarding the

Table 2.5 Estimated Likelihood of Misconduct, Peer Effects: Falsification Test

	DV: Prop. of former peers in $t-2$ with cases of misconduct in t				DV: Misconduct in t
	(1)	(2)	(3)		(4)
VARIABLES	GMM	GMM	GMM	VARIABLES	GMM
Prop. of peers in t-1 with misconduct	0.162	0.156	0.132	Prop. of peers in t-1 with misconduct	0.802*
	(0.136)	(0.153)	(0.155)		(0.346)
Gender (reference: Prop. of Females)				Gender (reference: Females)	0.014**
Prop. of Males	0.018***	0.018***	0.018***	Male	(0.004)
	(0.003)	(0.004)	(0.004)		
Employee type (reference: Prop. of Civil Staff)				Employee type (reference: Civil Staff)	
Prop. of Police Constable	0.027***	0.029***	0.030***	Police Constable	0.015~
	(0.004)	(0.005)	(0.005)		(0.008)
Prop. of Police Sergeant	0.027***	0.031***	0.034***	Police Sergeant	0.026***
	(0.005)	(0.006)	(0.006)		(0.008)
Prop. of Inspector	0.015**	0.021**	0.025***	Inspector	0.019*
	(0.006)	(0.007)	(0.007)		(0.009)
Prop. of Chief Inspector, Superintendent, Chief Superintendent	0.025**	0.022*	0.026*	Chief Inspector, Superintendent, Chief Superintendent	0.017~
	(0.009)	(0.010)	(0.010)		(0.010)
Prop. of Special Constabulary	-0.049***	-0.068***	-0.067***	Special Constabulary	-
	(0.006)	(0.013)	(0.013)		
Business Group (reference: Prop. in TP - Boroughs East)				Business Group (reference: TP - Boroughs East)	
Prop. in TP - Boroughs North	-0.004	-0.009*	-0.009~	TP - Boroughs North	-0.001
	(0.004)	(0.005)	(0.005)		(0.009)
Prop. in TP - Boroughs South	0.006~	0.005	0.005	TP - Boroughs South	0.001
	(0.004)	(0.004)	(0.004)		(0.008)
Prop. in TP - Boroughs West	-0.006	-0.007	-0.007	TP - Boroughs West	0.001
	(0.004)	(0.005)	(0.005)		(0.008)
Prop. in TP - Central	-0.011	-0.026	-0.022	TP - Central	-0.029*
	(0.019)	(0.027)	(0.027)		(0.013)
Prop. in TP - Criminal Justice & Crime	-0.006	-0.009~	-0.009~	TP - Criminal Justice & Crime	0.011
	(0.005)	(0.005)	(0.005)		(0.009)
Prop. in TP - Westminster	0.007	0.007	0.007	TP - Westminster	0.020
	(0.006)	(0.007)	(0.007)		(0.013)
Prop. in Specialist Crime and Operations	-0.028***	-0.030***	-0.029***	Specialist Crime and Operations	-0.002
	(0.005)	(0.005)	(0.005)		(0.010)
Prop. in Specialist Operations	-0.047***	-0.049***	-0.048***	Specialist Operations	-0.005
	(0.007)	(0.008)	(0.008)		(0.015)
Prop. in Other Business Group	-0.035***	-0.037***	-0.035***	Other Business Group	0.001
	(0.006)	(0.007)	(0.007)		(0.015)
Length of service				Length of service	
Average Length of service (10 years)	-0.026***	-0.034***	-0.039***	Length of service (10 years)	-0.022*
	(0.006)	(0.007)	(0.007)		(0.010)
Average Length of service (10 years)^2	0.003~	0.006**	0.007**	Length of service (10 years)^2	0.004
	(0.002)	(0.002)	(0.002)		(0.003)
Employee Rating in t-4 (reference: Competent but development required + Not Yet Competent)				Employee Rating in t-4 (reference: Competent but development required + Not Yet Competent)	
Prop. of Exceptional + Competent (above standard)		-0.079***	-0.080***	Exceptional + Competent (above standard)	-0.048*
		(0.023)	(0.023)		(0.021)
Prop. of Competent (at required standard)		-0.072**	-0.071**	Competent (at required standard)	-0.041~
		(0.023)	(0.023)		(0.021)
Constant	0.057***	0.136***	0.146***	Constant	0.054
	(0.010)	(0.024)	(0.025)		(0.033)
Observations	27,040	19,796	19,796	Observations	20,374
Number of individuals	18,506	14,111	14,111	Number of individuals	14,401
LM test statistic for underidentification (Kleibergen-Paap)	52.51	40.70	39.53	LM test statistic for under identification (Kleibergen-Paap)	35.16
P-value of under identification LM statistic	$p<0.001$	$p<0.001$	$p<0.001$	P-value of under identification LM statistic	$p<0.001$
F statistic for weak identification (Kleibergen-Paap)	25.39	19.62	19.09	F statistic for weak identification (Kleibergen-Paap)	16.98
Hansen Statistic	3.135	3.486	3.889	Hansen Statistic	0.0304
Degrees freedom of Hansen Statistic	1	1	1	Degrees freedom of Hansen Statistic	1
P value Hansen Statistic	0.0766	0.0619	0.0486	P value Hansen Statistic	0.862
Quarter FEs	NO	NO	YES	Quarter FEs	YES
Year FEs	NO	NO	YES	Year FEs	YES

Note. All models apply instrumental variable techniques for the identification of peer effects. Models 1 to 3 are part of a falsification test that study the behaviour of former peers of an individual i who moves to a different peer group in $t-1$. The outcome constitutes the proportion of these peers who had reports of misconduct at time t. The independent variable of interest is the proportion of peers of i in $t-1$ presenting incidence of misconduct. This variable is instrumented by two measures of conduct of peers of peers of i. By construction, these two measures are expected to have no influence on the outcome variable of these models. Model 4 is presented for comparative purposes and uses the standard outcome variable of the study, misconduct of i at time t. Robust standard errors in parentheses. Significance levels: *** p<0.001,** p<0.01, * p<0.05, ~ p<0.1.

effect of the control variables, across the different specifications they exhibit the expected signs and comparable sizes.

2.5 Estimation of Learning Effects

2.5.1 Econometric Model

The entire analysis thus far has concerned only the impact of learning from peers' misconduct, we now proceed to study the impact of disciplinary actions on future misconduct. The risk of events of misconduct for individual i in quarter t is represented now by a dynamic probit model where y_{it} is a binary outcome variable that denotes any allegation raised against i during quarter t. X is a matrix of explanatory variables that includes: sociodemographic characteristics, such as gender, length of service, employee's business group, employee type, and employee performance; line manager characteristics, such as supervisor performance and events of changes in supervisors; and additional controls for annual and seasonal effects.

$$y_{it} = 1[y_{i,t-1}\ Sanctions_{i,t-1}\ \rho + X_{it}\beta + \alpha_i + u_{it} > 0] \tag{2.2}$$

The model is dynamic as it allows the propensity of misconduct to be a function of the interaction between any previous incidence of misconduct, $y_{i,t-1}$ and the corresponding disciplinary actions that followed it, $Sanctions_{i,t-1}$. $Sanctions_{i,t-1}$ contains a set of dummies for the occurrence of 'no action', 'management action', 'formal action' and 'unknown action' in $t-1$. Due to their low frequency, actions that involve unsatisfactory performance procedures and the retirement of the workers were excluded from the analysis. In Equation 2.2, the term α_i captures the individual specific unobserved heterogeneity. It accounts for all time-invariant unobserved characteristics (e.g., individual differences such as stable personality traits) that might influence the propensity to misconduct. Observe that a major drawback of the related literature, which is mostly limited to cross-sectional data, is the failure to account properly for individual differences. Yet, it is well known that individuals' past behaviour is highly correlated with their future behaviour. Recall that in our data, as it is the case of many police departments' data, a small group of officers and civilian staff account for a disproportionate amount of cases of misconduct. It is then reasonable to assume that misconduct events are not independent.

This high degree of correlation among observations from the same individual can be the result of two non-mutually exclusive mechanisms: unobserved heterogeneity and state dependence (Heckman, 1981). According to the first of these mechanisms, individuals' probabilities to engage in misconduct might differ because of some latent and enduring personal characteristics, perhaps acquired early in life. In the criminology field, for example, the propensity to commit crime is related to lack of self-control, risk taking behaviour, impulsivity and low conscientiousness (Nagin and Paternoster, 1991, 2000). The alternative hypothesis, state dependence, implies that past experiences of misconduct have a genuine effect on the risk of future misconduct.

Equation 2.2 allows us to distinguish state dependence from unobserved heterogeneity. Testing the hypothesis of true state dependence is equivalent to testing whether the vector of coefficients ρ is non-zero. However, two common econometric difficulties are introduced once we allow the model to discriminate between these two aspects: how to treat the unobserved heterogeneity α_i and how to treat the initial conditions of the data, y_0 and $Santions_0$. Estimating a standard random effects model assumes zero correlation between the unobserved effect α_i and the set of explanatory variables X_{it}. Estimating a dynamic model when the time series is short relative to the cross-section size assumes that the initial conditions are uncorrelated with the unobserved heterogeneity. The failure to meet these assumptions could produce biased parameter estimates of the lagged dependent variable (Arellano, 2003; Nickell, 1981).

As both assumptions are further restrictive and unlikely to be met, we relax them as follows. The first assumption is relaxed following Mundlak (1978) and Chamberlain's (1984) suggestion that the unobserved heterogeneity is linear in the means of all the time varying covariates, $\alpha_i = \delta_0 + \bar{X}_i\delta + \varepsilon_i$, where ε_i is independent of X_{it}. We relax the second assumption using Wooldridge's (2005) conditional maximum likelihood estimator that models the distribution of the unobserved effect ε_i conditional on the initial value of the dependent variable and any exogenous explanatory variables. Thus, we define $\varepsilon_i = \varepsilon_0 + y_{i,0}\ Sanctions_{i,0}\ \omega + \epsilon_i$. Substituting into Equation 2.2 gives the final econometric specification used in our analysis:

$$y_{it} = 1[y_{i,t-1}\ Sanctions_{i,t-1}\ \rho + X_{it}\beta + \delta_0 + \bar{X}_i\delta + y_{i,0}\ Sanctions_{i,0}\ \omega + \epsilon_i + u_{it} > 0] \tag{2.3}$$

2.5.2 Results

Our main results are displayed in Tables 2.6 and 2.7. In Table 2.6, we begin by estimating Equation 2.2 using a probit model (Model 1) that uses as a dependent variable a binary indicator of misconduct in a given quarter and, as independent variables, the lagged records of misconduct and disciplinary actions received. Models 2 to 6 are dynamic correlated random effects models (CRE) that follow Equation 2.3 and so these models include a full set of controls for the means of all the time varying covariates and dummies for the initial conditions of the data. From Model 3, we add different control variables to test the stability of our results. However, as some of these controls variables could be simultaneously determined (e.g., employee performance being simultaneously determined with the line manager performance), we test their effects in separate models.

Model 3 includes controls for gender, length of service, employee's business group, and employee type. Model 4 replicates Model 3 but adds controls for supervisor performance. Model 5 replicates Model 3 but adds controls for employee performance. Model 6 replicates Model 3 but incorporates controls for any change in supervision during the preceding year. Arguably, changes in line manager might have co-occurred with changes in peers. We capture these confounds with a vector of dummies that reflect the percentage of current peers that remain working with individual i during the preceding year. These dummies are part of the control variables used in Model 6. All models incorporate controls for annual and seasonal effects.

As the standard probit model (Model 1) and the CRE models (Models 2–6) involve different normalizations, to compare the estimates we need to multiply the CRE coefficients by $\sqrt{1 - ICC}$, where ICC is the intraclass correlation coefficient (Arulampalam, 1999). For instance, the scaled coefficient of Model 2, for formal actions, management actions and no actions, are -0.173, 0.116 and 0.095, respectively. The scaled coefficients for the remaining Models 3–6 are similar in magnitude. Therefore, assuming that the individual heterogeneity is orthogonal to the explanatory variables and that the initial conditions of the data are exogenous—the assumptions implicit by Model 1—inflates substantially the effect of state dependence. Observe that the scaled CRE coefficients from Models 2–6 are less than one fourth of the Model 1 probit estimates and even reverse sign (such as in the case of the coefficients for formal actions). Because the assumptions for Model 1 are violated, the estimates from Models 2–6 should be used. Note that the estimates of the ICC from Model 3 and onwards imply that approximately 12% of the total error variance is attributable to individual unobserved heterogeneity.

Overall, the estimates from Models 2-6 in Table 2.6 suggest that the exposure to complaints that were followed by formal actions appear to discourage misconduct events, while the opposite occurs with any other disciplinary action. Before we consider the size of this learning effect, we introduce a second analysis including only individuals with a previous history of misconduct—a group of individuals who are expected to be less heterogeneous. Table 2.7 replicates Table 2.6 for this group. The effect of disciplinary actions is stronger in this group and, as before, remains robust to the inclusion of socioeconomic and contextual controls.

For the models in Tables 2.6 and 2.7, the effect of covariates are in line with the findings of other studies in the literature: male workers, police officers and less experienced employees are prone to receive more allegations of misconduct. We also see expected signs, though non-significant, for a positive effect of previous performance reviews, positive effects for exposure to competent supervisors, and negative effects for changing supervisors. It is not surprising, however, that the supervisors' behaviour could influences his subordinates' willingness to engage in misconduct, since evidence suggest that leaders play a crucial role in disseminating organizational misconduct, as they could authorize misconduct explicitly or implicitly, by allowing or rewarding it (Greve et al., 2010).

The probabilities of misconduct at time t conditional on the status at $t-1$ for the whole sample and for the sample of individuals with antecedents of misconduct are presented in Figure 2.5. The black circles show the conditional probabilities of misconduct at t fitted from Model 3 (Tables 2.6 and 2.7) and bars indicate 95% confidence intervals. The red dotted lines provide the baseline for comparisons, that is the probability of current misconduct in absence of learning effects (i.e., when misconduct in $t-1$=0). The predictions from the Individuals-with-History-of-Misconduct-Graph shows that the probability of misconduct at t is much higher for those receiving management actions than no actions at $t-1$: Someone exposed to a management action at $t-1$ increased his or her likelihood of misconduct from 11.3% to 13.0% (i.e., 1.15 times more likely). Crucially, someone exposed to a formal action in $t-1$ decreased his or her likelihood of misconduct from 11.3% to 7.3% (i.e. 1.55 times less likely). To compare estimates with raw data in Figure 2.5, diamonds display the conditional raw proportions. It is reassuring to note that, for the Individuals-with-History-

Table 2.6 Estimated Likelihood of Misconduct, Past Misconduct Effects

VARIABLES	(1) PROBIT	(2) CRE	(3) CRE	(4) CRE	(5) CRE	(6) CRE
Sanctions						
Formal Action in $t-1$	0.150**	-0.196***	-0.062	-0.138~	-0.190**	-0.101
	(0.053)	(0.058)	(0.057)	(0.076)	(0.074)	(0.088)
Management Action in $t-1$	0.456***	0.131***	0.174***	0.169***	0.157***	0.196***
	(0.026)	(0.028)	(0.027)	(0.036)	(0.035)	(0.041)
No Action in $t-1$	0.546***	0.108***	0.091***	0.077***	0.078***	0.078***
	(0.012)	(0.013)	(0.013)	(0.017)	(0.017)	(0.020)
Unknown Action in $t-1$	0.444***	0.028	0.031	0.078	0.014	0.073
	(0.040)	(0.044)	(0.043)	(0.048)	(0.048)	(0.049)
Gender						
(reference: Female)						
Male			0.178***	0.165***	0.178***	0.171***
			(0.009)	(0.010)	(0.010)	(0.012)
Length of service						
Length of service (years)			-0.321***	0.139*	0.137	0.180
			(0.031)	(0.060)	(0.657)	(0.806)
Length of service (years)^2			0.000*	0.001~	0.001***	0.001*
			(0.000)	(0.000)	(0.000)	(0.001)
Business Group						
(reference: TP - Boroughs East)						
TP - Boroughs North			-0.019	-0.011	0.002	-0.010
			(0.016)	(0.018)	(0.018)	(0.020)
TP - Boroughs South			0.023	0.055***	0.055***	0.050**
			(0.015)	(0.016)	(0.017)	(0.018)
TP - Boroughs West			-0.012	-0.004	0.007	0.000
			(0.016)	(0.017)	(0.017)	(0.019)
TP - Central			-0.085	-0.172	-0.882*	-0.107
			(0.128)	(0.263)	(0.347)	(0.216)
TP - Criminal Justice & Crime			-0.070***	-0.045*	-0.035*	-0.018
			(0.015)	(0.018)	(0.017)	(0.020)
TP - Westminster			-0.017	0.021	-0.000	-0.007
			(0.023)	(0.027)	(0.026)	(0.028)
Specialist Crime and Operations			-0.274***	-0.250***	-0.276***	-0.271***
			(0.013)	(0.016)	(0.015)	(0.018)
Specialist Operations			-0.547***	-0.550***	-0.545***	-0.526***
			(0.018)	(0.022)	(0.020)	(0.025)
Other Business Group			-0.666***	-0.673***	-0.669***	-0.651***
			(0.023)	(0.031)	(0.028)	(0.035)
Employee type						
(reference: Civil Staff)						
Police			0.475***	0.421***	0.460***	0.369***
			(0.012)	(0.014)	(0.014)	(0.016)
Special Constabulary			-0.495***	-0.561***		-0.642***
			(0.032)	(0.042)		(0.043)
Employee Rating in $t-4$						
(reference: Competent but development required + Not Yet Competent)						
Exceptional + Competent (above standard)					-0.081	
					(0.055)	
Competent (at required standard)					-0.075	
					(0.053)	
Line Manager Rating in $t-4$						
(reference: Competent but development required + Not Yet Competent)						
Exceptional + Competent (above standard)				-0.166		
				(0.117)		
Competent (at required standard)				-0.165		
				(0.117)		
Change Line Manager during $t-4$ to $t-7$						0.013
						(0.014)
Constant	-1.802***	-2.043***	-2.768***	-1.371***	-1.140	-1.873*
	(0.011)	(0.013)	(0.074)	(0.237)	(1.071)	(0.807)
$\ln \sigma_u^2$		-1.274***	-1.880***	-1.972***	-1.944***	-1.998***
		(0.023)	(0.030)	(0.047)	(0.041)	(0.057)
Observations	608,220	608,220	608,220	339,943	385,838	263,600
Log likelihood	-107061	-103638	-98993	-62126	-67907	-48788
Number of individuals		40,548	40,548	42,061	36,992	38,277
ICC		0.219	0.132	0.122	0.125	0.119
σ_u		0.529	0.391	0.373	0.378	0.368
Quarter FEs	YES	YES	YES	YES	YES	YES
Annual FEs	YES	YES	YES	YES	YES	YES
% Change in peers that coincided with the change in Line Manager FEs						YES

Note. Sample include individuals with records from 2011q2 to 2014q4. All the models are dynamic models in which the outcome takes the value of one when at least one event of misconduct occurred in quarter t. Model 1 is a pooled probit model, Models 2 to 6 are CRE models that account for individual heterogeneity. Model 6 evaluates the effect of a change in line manager in the preceding year and includes dummy controls for every decile of peers that remained working with the employee at the end of the preceding year (i.e, at $t-4$). Standard errors in parentheses. Significance levels: *** p<0.001,** p<0.01, * p<0.05, $\sim$ p<0.1.

Table 2.7 Estimated Likelihood of Misconduct, Past Misconduct Effects, Individuals with at Least One Complaint

VARIABLES	(1) PROBIT	(2) CRE	(3) CRE	(4) CRE	(5) CRE	(6) CRE
Sanctions						
Formal Action in $t-1$	-0.304***	-0.299***	-0.241***	-0.338***	-0.371***	-0.346***
	(0.052)	(0.052)	(0.053)	(0.072)	(0.067)	(0.082)
Management Action in $t-1$	0.076**	0.083**	0.087***	0.084*	0.085**	0.108**
	(0.025)	(0.025)	(0.025)	(0.034)	(0.032)	(0.039)
No Action in $t-1$	0.041***	0.044***	0.018	0.004	0.009	0.009
	(0.012)	(0.012)	(0.012)	(0.016)	(0.015)	(0.019)
Unknown Action in $t-1$	-0.016	-0.017	-0.032	0.001	-0.041	0.002
	(0.040)	(0.040)	(0.040)	(0.048)	(0.045)	(0.048)
Gender (reference: Females)						
Male			0.078***	0.068***	0.077***	0.074***
			(0.008)	(0.010)	(0.009)	(0.011)
Length of service						
Length of service (years)			-0.775***	-1.748***	-1.863*	-16.652*
			(0.054)	(0.192)	(0.898)	(7.335)
Length of service (years)^2			0.001**	0.001**	0.001***	0.001~
			(0.000)	(0.000)	(0.000)	(0.001)
Business Group						
(reference: TP - Boroughs East)						
TP - Boroughs North			-0.006	-0.005	-0.004	-0.010
			(0.013)	(0.017)	(0.015)	(0.018)
TP - Boroughs South			0.019	0.039*	0.034*	0.030~
			(0.012)	(0.015)	(0.014)	(0.017)
TP - Boroughs West			-0.004	0.015	0.004	0.013
			(0.013)	(0.016)	(0.015)	(0.018)
TP - Central			0.118	0.025	-0.462~	0.062
			(0.139)	(0.263)	(0.263)	(0.179)
TP - Criminal Justice & Crime			-0.046***	-0.027	-0.034*	-0.021
			(0.013)	(0.016)	(0.015)	(0.019)
TP - Westminster			-0.021	0.004	-0.022	-0.001
			(0.019)	(0.025)	(0.022)	(0.027)
Specialist Crime and Operations			-0.093***	-0.092***	-0.105***	-0.124***
			(0.012)	(0.014)	(0.013)	(0.016)
Specialist Operations			-0.172***	-0.215***	-0.196***	-0.225***
			(0.017)	(0.020)	(0.018)	(0.023)
Other Business Group			-0.173***	-0.173***	-0.196***	-0.207***
			(0.026)	(0.027)	(0.024)	(0.035)
Employee type (reference: Civil Staff)						
Police			0.111***	0.060***	0.073***	0.002
			(0.011)	(0.013)	(0.011)	(0.015)
Special Constabulary			-0.171***	-0.239***		-0.326***
			(0.036)	(0.048)		(0.046)
Employee Rating in $t-4$						
(reference: Competent but development required + Not Yet Competent)						
Exceptional + Competent (above standard)					-0.085	
					(0.058)	
Competent (at required standard)					-0.077	
					(0.057)	
Line Manager Rating in $t-4$						
(reference: Competent but development required + Not Yet Competent)						
Exceptional + Competent (above standard)				-0.208		
				(0.149)		
Competent (at required standard)				-0.205		
				(0.149)		
Change Line Manager during $t-4$ to $t-7$						0.027~
						(0.016)
Constant	-1.285***	-1.278***	-3.064***	-3.958***	-4.028**	-17.816*
	(0.013)	(0.013)	(0.124)	(0.356)	(1.460)	(7.336)
$\ln \sigma_u^2$		-15.940**	-14.846***	-13.220	-15.679	-12.632
		(6.014)	(3.275)	(2,872.481)	(29,759.415)	(1,925.019)
Observations	233,250	233,250	233,250	133,620	156,740	105,794
Log likelihood	-82088	-82070	-81604	-47749	-56015	-38195
Number of individuals		15,550	15,550	15,213	14,869	14,401
ICC		1.19×10^{-7}	3.57×10^{-7}	1.81×10^{-6}	1.55×10^{-7}	3.27×10^{-6}
σ_u		0.000346	0.000597	0.00135	0.000394	0.00181
Quarter FEs	YES	YES	YES	YES	YES	YES
Annual FEs	YES	YES	YES	YES	YES	YES
% Change in peers that coincided with the change in Line Manager FEs						YES

Note. Sample include individuals with records from 2011q2 to 2014q4 and is restricted to those individuals with antecedents of misconduct. All the models are dynamic models in which the outcome takes the value of one when at least one event of misconduct occurred in quarter t. Model 1 is a pooled probit model, Models 2 to 6 are CRE models that account for individual heterogeneity. Model 6 evaluates the effect of a change in line manager in the preceding year and includes dummy controls for every decile of peers that remained working with the employee at the end of the preceding year (i.e, at $t-4$). Standard errors in parentheses. Significance levels: *** p<0.001,** p<0.01, * p<0.05, ~ p<0.1.

of-Misconduct-Graph—where the heterogeneity is low—the simple conditional proportions tightly coincide with the model predictions. These findings provide support to the hypothesis that reinforcement facilitates learning and agree with the commonly accepted ideas that punished behaviour tends to be discontinued while rewarded behaviour is strengthened (Thorndike, 1898, 1927).

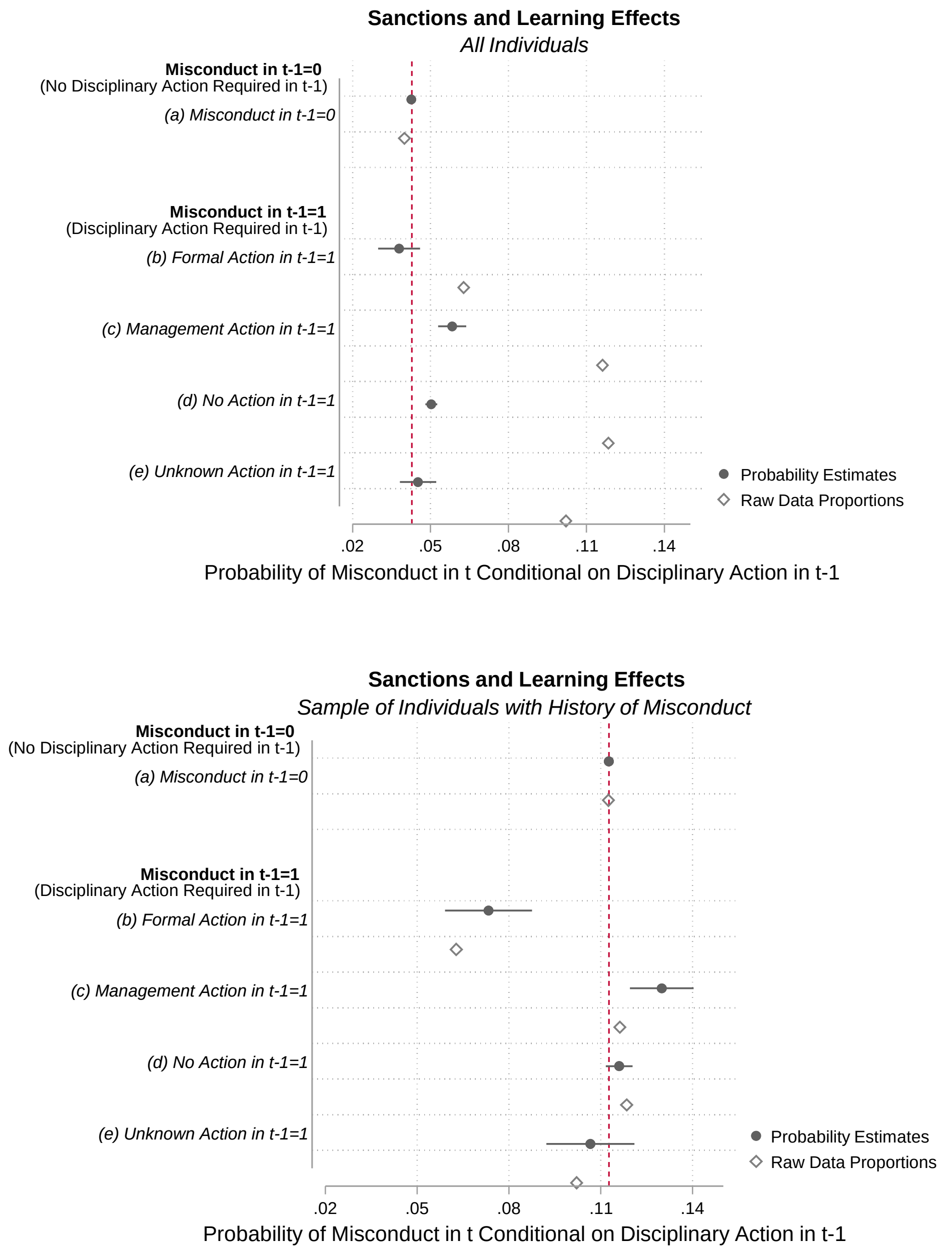


Fig. 2.5 The effects of recent incidence of misconduct on current misconduct. The panels display fitted conditional probabilities of misconduct at t given misconduct at $t-1$. The top panel includes all individuals (estimates come from Model 3 of Table 2.6). The bottom panel includes those individuals with records of misconduct (estimates come from Model 3 of Table 2.7). Circles display the conditional probabilities given a specific sanction in $t-1$ (i.e., no other type of sanction took place in $t-1$). The red dotted lines show the baseline for comparisons, that is the probability of current misconduct in absence of learning effects (i.e., no misconduct occurred in $t-1$). Lines span 95% confidence intervals. To compare estimates with raw data, diamonds display the conditional raw proportions.

2.6 Summary and Caveats

To summarize our results, there are two key insights from our study. First, peer effects are nontrivial. An individual who has a 10% increase in the fraction of peers with misconduct (e.g., when a complaint prone person is transferred to their existing group of 10) has his risk of misconduct raised by an absolute 8 percentage points. Second, misconduct events are mediated by the experience of recent disciplinary actions. In particular, only formal disciplinary actions appear to discourage future misbehaviour. For officers with a history of complaints, formal disciplinary actions in the previous quarter reduces the chances of misconduct in the current quarter from 11.3% to 7.3%. In addition, we also replicate the individual differences that are associated with misconduct. In consistency with earlier research, we found that certain demographic characteristics are consistently present in individuals with higher risk of misconduct, such as few years of experience, poor ratings of past performance, poor line manager performance, male gender, or certain employee types (like police sergeant and constable).

Before turning to the main conclusions of the study, we must highlight a few caveats. First, we have taken complaints filed against officers as an accurate approximation of misconduct events. Yet, these complaints could either over or under represent real misconduct cases. For example, fellow officers, as opposed to citizens, fail to report misconduct due to their cultural rules of integrity. Informally, the “Code” discourages them from reporting misconduct of their peers (Klockars et al., 1997; Wolfe and Piquero, 2011). On the other hand, citizen allegations of misconduct may be discouraged when there is fear of retaliation or a low confidence in the complaint process (Lersch, 2002). Our data, however, does not allow us to distinguish the source of the complaints. There is also concern about whether the frequency of complaints mirrors officers’ productivity. There is evidence suggesting that more proactive officers, officers placed in areas with high crime rates, and officers that due to their patrol assignment are more likely to be in contact with citizens, are prone to receive citizen’s allegations of misconduct (Harris, 2009; Lersch, 2002). Unfortunately, we were not able to control for the officers’ arrest activity. However, to the extent that some degree of arrest activity might be associated to time-invariant individual characteristics, or characteristics that might have remained relatively stable over the four-year interval of available data, such as rank hierarchy or the assignment to different police units, we do capture the effects of individual productivity.

2.7 Discussion and Conclusions

This paper/chapter adds to a growing list of studies on police misconduct. Unlike many earlier studies, we used a rich dataset that allowed us to identify officers, their peers and their immediate supervisors for a four-year interval. Our findings demonstrate that deviant behaviour can be learnt through socialization and can be reduced through disciplinary action: The exposure to complaint prone peers increases the risk of future misconduct; however, formal sanctions after an event of misconduct reduce such risk.

It appears that officers are inclined to engage in behaviour that they have recently witnessed their immediate peers doing. Perhaps their beliefs about what is acceptable and unacceptable behaviour became more permissive when they become part of closely connected groups. Following, Ashforth and Anand (2003), because life is lived in concrete settings, localized social cultures tend to be highly salient, and the individual's commitment to ethics may relax under the press of local circumstances. Moreover, local groups often provide accounts to rationalize or neutralize the guilt that individuals engaging in misconduct might otherwise feel, such as denial of the victim, denial of injury, denial of responsibility, and refocusing attention, among other accounts.

While a discussion of the mechanisms behind police peer effects is beyond the scope of our research, it is worth commenting on the most recent findings in the literature provided by Hough et al. (2018). The authors examined cases of alleged misconduct involving chief police officers in England and Wales over a six-year period, up to 2013, and interviewed stakeholders, police officers and other personnel who had investigated chief officer misconduct. Their interviews suggest that, throughout their careers, police officers felt under pressure to not step outside the norm. The ethical climate, promoted by a typical command-and-control style of management, is alleged to lack ethical values or, even worse, to sustain the wrong kinds of values. The command-and-control style of management appears to encourage close mutually supportive and inward-looking networks that favour homogeneity, preclude difference and even accept or tolerate bullying behaviour. The attitudes and values shaped under this climate might explain why only severe sanctions have been found to have some deterrent effect. Hough et al's findings suggest that there is little to no stigma associated with misconduct in the police culture. Therefore, management actions or any other less severe disciplinary action might likely have very little deterrent effect on bad cops.

Our peer effect results are to some extent consistent with the work of Chappell and Piquero (2004), Getty et al. (2014), and Ingram et al. (2013), who suggested that peer effects are important determinants of misconduct based on correlational studies, and lend also support to differential association theory, according to which criminal behaviour can be learnt through long, frequent and intense interactions with individuals holding attitudes that encourage criminal activity (Akers, 2013).

Our confidence in our results is justified by the fact that they are robust to the inclusion of several contextual control variables and different specifications. Although it seems intuitive that individuals' experience and the social context in which they operate can influence their behaviour, to the best of our knowledge this is a finding that has not previously been demonstrated convincingly in police misconduct research, due to the lack of longitudinal data or the omission of individual heterogeneity.

Chapter 3

The Red, the Black, and the Plastic: Paying Down Credit Card Debt for Hotels Not Sofas

3.1 Introduction

The assumption of fungibility is an essential feature of standard consumer theory. Consumers are assumed to purchase what they value most, and to pay for their purchases using the least costly options for payment. What a person pays for should not affect how they pay for it (e.g., via cash or credit), and how money is obtained should not affect the way it is spent. Research on mental accounting (Thaler, 1999) challenges these assumptions. There is by now a large body of empirical research documenting violations of fungibility, showing that people like to pay for different types of purchases in different ways, and that people like to spend money arising from different sources, or stored in different ways, differently (for a discussion of the assumption of fungibility in standard economics see Thaler, 1985).

Most of the early research on mental accounting involved surveys and hypothetical choice studies. O'curry and Strahilevitz (2001) found that, compared to ordinary income, windfall gains, including winnings from longshot lotteries, are more likely to be spend on hedonic, as opposed to utilitarian, goods. Thaler and Johnson (1990) report the phenomenon, since well documented (Ackert et al., 2006; Keasey and Moon, 1996; Weber and Zuchel, 2005), that gamblers are more willing to take risks after a recent gain since they feel they are playing with house money. Heath and Soll (1996) find that when consumers purchase an item that is prototypical of an expense category, they are subsequently less likely to purchase other items in that category, which they attribute to non-fungibility between mental accounts.

A number of field studies have subsequently documented diverse violations of fungibility (for a recent review see Zhang and Sussman, 2018). Virtually all of these focus on the question of whether money that is framed as coming from, or designated as being earmarked for, a specific category of consumption is, in fact, spent on that category (as discussed by Thaler, 1985). Kooreman (2000), in an early field study, found that the marginal propensity to consume child clothing out of child benefits is higher than out of other income. Beatty et al. (2014), using a regression discontinuity analysis, find that the UK Winter Fuel Payment, a cash grant, is disproportionately spent on heating. Hastings and Shapiro (2017), using a data set of grocery transactions that include information about payment medium, find that Supplemental Nutrition Assistance Program (SNAP) payments are disproportionately spent on food, relative to cash income. Milkman and Beshears (2009) find that a grocery coupon provided by an online retailer leads to a much greater increase in spending on food than that which is predicted by standard economic theory. Finally, whereas all the studies just reviewed relied on observational field data, Abeler and Marklein (2017) conducted a field experiment in which patrons of a wine restaurant were given a coupon good for either any usage or for wine. Customers given the wine coupon spent more on wine than those given the coupon earmarked for any usage and both groups spent more on their overall meal. Both results violate fungibility (given that virtually all patrons of the wine restaurant would have spent at least the value of the coupon on wine).

We used data from a large data set on credit card spending to test a major prediction of a theory of mental accounting proposed by Prelec and Loewenstein (1998): that consumers will be more motivated to pay off expenditure on more transient forms of consumption more quickly than expenditures on durables. We provide the first field test of this theoretical prediction using transaction and repayment data from a sample of 1.8 million credit card accounts. In line with the predictions of Prelec and Loewenstein, we find that people are an absolute 10% less likely to pay off, and hence more likely to pay interest on, durable items like vehicles, clothes and education, compared to non-durable items like grocery products, gas, hotel accommodation, and restaurants. This result holds in analyses comparing repayments across individuals and also analyses comparing changes in repayments within individuals over time (with individual fixed effects). As a complement to the judgments of hypothetical scenarios presented in Prelec and Loewenstein, our field data are the first evidence that debt aversion varies as a function of the nature of the associated consumption, and the first evidence regarding preferences for the relative timing of consumption and payment.

Prior research has examined patterns of behaviour involving credit cards using diverse research methods and data sources. For example, in incentivized laboratory experiments, Amar et al. (2011) found that consumers were more likely to spend on credit cards with the lowest balance rather than, as cost-minimization would suggest, the lowest rate of interest. Stewart (2009) (see also Keys and Wang, 2016; Navarro-Martinez et al., 2011) examined, using both credit card repayment data and an experiment, whether consumers anchor repayments on minimum payment amounts that are currently included on all credit card statements. Gathergood et al. (2017) (see also Ponce et al., 2017; Stango and Zinman, 2009) examined how consumers split repayments across debts held over multiple cards. All three contributions show that consumers tend not to minimize interest costs when allocating repayments across cards and Gathergood et al. (2017) show that this arises because consumers tend to split the ratio of repayments across their cards in approximate proportion to the ratio of revolving balances, instead of paying down the highest interest rate debt first, as economic logic would predict. Using detailed transactions data from a relatively affluent and financially sophisticated online panel of 917 households, Stango and Zinman (2009) found that the median household pays $500 per year in credit card costs and could avoid more than half these costs with minor changes in behaviour. In contrast to these prior contributions, the current paper is, to the best of our knowledge, the first to use credit card data to test for a violation of fungibility, as well as the first to test a key prediction of the Prelec and Loewenstein (1998) model using field data. Rather than examining the impact of credit balances and APRs on card repayment, here we examine the impact of the specific type of consumption financed with a credit card on the likelihood of fully paying off the credit balance on the card.

Beyond providing support for a key prediction of Prelec and Loewenstein, our results have implications for the designers of financial products. In particular, if customers have a preference for paying down certain types of consumption ahead of others, customers may value payment options which allow them to prioritize payments against certain spending types. Credit card issuers currently report customer card balances, with manual and automated payment options at various level of payment (including minimum payment or full payment), but customers might also benefit from options which allow them to identify the balance due by the spending it represented, and then pay for specific items. The research reported here suggests that, given such an option, consumers would be prone to pay off debt incurred for non-durable than for durable consumption, and that doing so might well decrease the pain they experience from paying off their credit card. More generally, managers should look for ways to reduce customers' and workers' pain of paying to enhance the value of incentives that they provide. For example, if customers find it painful to pay for shipping on purchases, a promotional offer could be framed as paying for, or providing free, shipping as opposed to a discount from the price of the product itself. Or, if gas prices are high and consumers find it painful to pay for their daily commute, a wellness program that provided incentives in the form of gas cards might be more effective than one that paid the same amount in cash, despite the compelling economic logic favoring cash that can be spent in a maximally flexible fashion.

3.2 Background

Prelec and Loewenstein (1998) propose a double mental accounting model in which people establish mental accounts to link the *pleasure* of the consumption of an item with the *pain* of payment for it. In their model, every act of consumption evokes painful consideration of its cost, and every act of payment is buffered by (typically) pleasurable thoughts about the consumption that the payment is financing. The key assumption of the model, dubbed *prospective accounting*, is that people only care about future costs and benefits: For each transaction, people offset the pain of repayments against future consumption, and offset the pleasure of consumption against the pain of future repayments. Prospective accounting predicts, for example, that a vacation paid for ahead of time will be more enjoyable because, since there are no payments in the future, it feels as if it is free. Likewise, it predicts that paying for the vacation after one returns will be especially painful because, given that the vacation has already happened in the past, it feels as if one is paying for nothing. Purchase and repayment decisions are, therefore, contingent on the expected sequence of consumption and payment utilities. When a good is not fully paid off, or when a transaction is made in multiple payments, the pleasure of its consumption is undermined by painful thoughts regarding the remaining payments. Hence, consumers would be inclined to prepay for a product rather than accumulate the debt.

However, the attractiveness of prepayments is not the same for all types of consumption in the double mental accounting model. People are happier to pay interest on durable goods because the pain of paying interest is offset by their anticipated future consumption from the durable good. But for non-durable goods that are consumed immediately, as in the vacation example above, there is no future consumption to offset the pain of paying interest. Hence people have a stronger preference for prepaying debt associated with non-durable goods compared with durable goods.

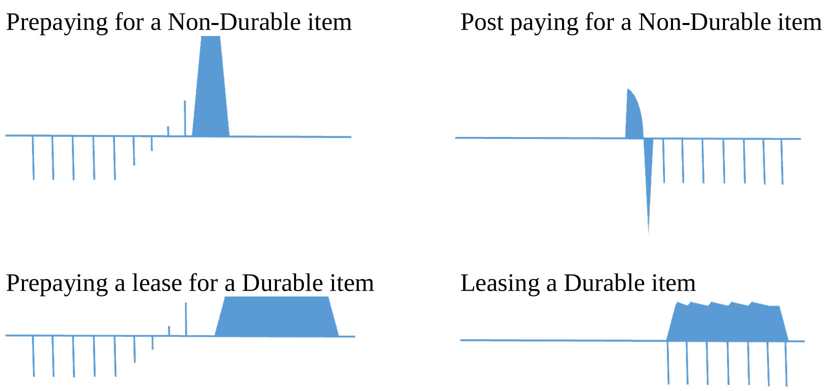


Fig. 3.1 Impact of prepayment (left) or post-payment (right) on the hedonics of consumption and payment for a non-durable good (top) and a durable good (bottom). The shaded area is experienced utility of consumption and the bars are the experienced disutility of the payments as predicted by the Mental Accounting Model (Prelec and Loewenstein, 1998). Redrawn from Prelec and Loewenstein (1998) Figure 4.

Figure 3.1 illustrates the interaction between the magnitude of hedonic benefits of prepayment and the durations of the utility flow. The top panels represent the utility flow obtained when prepaying (left) and post-paying or leasing (right) a non-durable item with high utility, such as the vacation. The bottom panel illustrates the equivalent utility flow for a durable item, such as a clothes dryer. The shaded area indicates the net utility derived from consumption after subtracting the disutility associated with the future payments. The vertical bars record the net disutility of payments after subtracting the utility related to future consumption.

When the payment schedule for the vacation is shifted into the future, there is a large hedonic fall at the very end of the vacation since there are only payments to look forward to. In contrast, there is little psychological cost to delaying the payments for the clothes dryer, as the dryer delivers sufficient residual utility over its lifetime. So, the mental account approach predicts a strong tendency to accelerate payment for items whose utility declines over time. Note that consumers may also prefer not to pay in advance for durable goods, so that they can maintain the ability to withhold payments for durable goods that later break down (Patrick and Park, 2006).

Prelec and Loewenstein (1998) show, for instance, that although prepayment would greatly enhance the quality of a vacation experience, it would have a small or negligible influence on the hedonics obtained from the use of a clothes dryer. In one of their studies, they described two scenarios to 91 visitors to the Phipps Conservatory in Pittsburgh. In the first scenario, the visitors were asked to imagine they were planning a one-week vacation to the Caribbean, six months from now, that will cost $1,200. They could finance the vacation by either a six-monthly payment of $200 before the beginning of the vacation or a six-monthly payment of $200 after returning. About 60% of respondents chose the earlier payments. However, in the second scenario, when they were asked to imagine that they were planning to purchase a clothes washer and dryer that will cost $1,200 and that they could finance it by either six monthly payments of $200 before the machine arrives or by six monthly payments beginning after it arrives, 84% of visitors opted to postpone the payments.

In summary, to keep mental accounts in the black, people are prone to accelerate payments for items whose utility declines overt time (non-durables), but will be less motivated to do so with items whose utility persists over time (durables). Mental accounting may act at the time of repayment, encouraging people to repay debt on non-durable items when they receive their bill, or it may at the time of purchase, so that people avoid spending on non-durable items they cannot immediately afford because they anticipate the greater pain of repaying. Either way, the prediction is the same. People should be more likely to repay debt incurred on non-durable items. To test this prediction, we consider different spending and repayment patterns in which individuals might link their propensity to repay their credit card bill to the type of consumption that created the bill.

We begin by analysing repayment patterns in new credit card accounts that begin with no debt and incur spending of a single purchase type only —durable or non-durable— during the month. Using a classification proposed by Kuchler (2013), we categorize spending into durable and non-durable purchases from 25 underlying merchant categories of expenditure. Kuchler lists short-run consumables and other non-durable spending categories (see Kuchler, 2013, p. 46). We used this list to assign our merchant category codes to durable and non-durable categories. For example, 'airlines' are classified as non-durable and 'electric appliance stores' are classified as durable. We test the sensitivity of our results to re-classification of categories which might arguably contain both durable and non-durable items. In response to a reviewer's comments we also ran a consumer survey of 501 UK residents, measuring the durability of 152 goods and services from the 25 merchant categories. These ratings lead to a durable/non-durable classification that is very similar to Kuchler's.

We evaluate how the nature of the spending increases or decreases the likelihood of full repayment of the debt. Regression analysis shows that individuals who spend on non-durable goods are almost 9 percentage points more likely to pay the bill in full at the end of the month. Durable goods are often big ticket items, so we control for the size of the credit card balance using a fifth-order polynomial and also conduct separate regressions across samples by quartile of the balance amount. This result also holds when additional controls are added to the regression specification, including characteristics of the credit card account (including the Annualised Percentage Rate (APR) and credit limit) and controls for matched socio-economic characteristics of the postcode of the card holder obtained from census data. The postcode level control variables allow us to control, albeit imperfectly, for differences in socio-economic characteristics (e.g. incomes) which might determine credit card repayment behaviour.

We then expanded our analysis to evaluate repayment behaviour of accounts which show spending on both durables and non-durables within the month. Specifically, we quantify how the probability of full repayment is related to the proportion of total spending of each type within the month. Results show the same effect as in the single purchase type analysis, the coefficient estimates implying that a switch from the percentage of purchases in the non-durable category from 0% to 100% increases the likelihood of full repayment of the credit card bill by 15 percentage points. This result is again robust to the inclusion of controls for account balance amount, credit card account characteristics and socio-economic characteristics.

In subsequent analyses, we expand the data sample to include older credit card accounts and again conduct analysis of months of data in which accounts incur spending of a single purchase type and multiple purchase types. These samples provide multiple observations of spending and repayment undertaken by the same individual over time. With these data we are able to estimate models which include random and fixed effects. The inclusion of individual fixed effects allows us to control for individual-specific time-invariant unobserved heterogeneity, which might drive differences in repayment behaviours across individuals, such as differences in permanent incomes or Intelligence Quotient (IQ). These models allow us to control for unobserved heterogeneity across individuals, such as an underlying propensity to repay an account in full (which might correlate with the type of spending). We find that our central result is robust to the inclusion of either random effects or individual fixed effects.

Unfortunately, conducting a field experiment on the question this paper addresses would be difficult if not impossible because we cannot experimentally assign debts accruing from spending on durable or non-durable goods to a sample of credit card holders in real world data. While Prelec and Loewenstein (1998) examined closely related questions by presenting experimental subjects with hypothetical scenarios, in real world data we are limited to observing natural occurring variation in spending over time, which has inevitable limitations. Specifically, it is difficult to definitely rule out potential confounds, such as individual differences which might lead to differences in repayment behaviour. Our data do allow us to control for a rich set of time-varying credit card account characteristics, socio-economic characteristics and individual fixed effects. The inclusion of individual fixed effects allows us to allay a concern with models exploiting variation across individuals that some individuals might be inherently more likely to repay than others due to differences in time preferences and this might also explain their tendency to purchase durables instead of non-durables. Nevertheless, our data do not allow us to account for selection into credit card spending for durable and non-durable goods. For example, individuals may be more likely to put spending on non-durable goods they intend to repay straightaway onto their credit card than they are to put spending on durable goods they intend to repay straightaway.

3.3 Data and Estimation Strategy

3.3.1 Credit Card Data

Our data source is the Argus Information and Advisory Services' "Credit Card Payments Study" (CCPS). The Argus data contains detailed records of credit card transactions (including spending and repayments), contract terms (e.g.

APR and credit limits) and billing records (including minimum payments due and billing dates). We have a subset of data from five large UK credit card issuers. Together these issuers have a market share of over 40%. We use a 10% representative sample of all individuals in the CCPS who held a credit card between January 2013 and December 2014 with at least one of the five issuers. This data sample provides approximately 1.8 million cards. The UK credit card market is similar to the US in many respects. Visa and Mastercard are the most dominant card networks. The most widely issued credit cards are the general purpose credit cards, which offer comparable features and fee structures and often include rewards programs, teaser rate deals and balance transfer facilities. Moreover, some UK card issuers are subsidiaries of US firms (e.g., Barclaycard, Capital One, etc).

3.3.2 Purchases of Durable and Non-Durables

The data include detailed records of card spending incurred each month in 25 merchant coded categories, such as 'restaurant / bars', 'food stores' and 'vehicles'. We classify each category as 'durable' or 'non-durable', closely following the classification used in Kuchler (2013). For example, 'airlines' and 'hotels services' are classified as non-durable; while purchases made in 'clothing stores' and 'electric appliance stores' are classified as durable. Table 3.1 provides a breakdown of the classification of the categories into the two spending types. Some spending categories might contain purchases of both durables and non-durables, such as the 'other retail' and 'discount stores' categories. In a subsequent analysis, we test the sensitivity of our results to re-classification of categories which might contain both durable and non-durable items and to a re-classification based upon consumer's judgments of durability.

3.3.3 Sample Selection

Our interest in this paper is in the relationship between types of credit card spending and subsequent repayment behaviour. The unit of analysis is a month of data in which we observe the spending and repayment on an account. We therefore first restrict the sample to months in which (a) spending is incurred on the account in either the durable or non-durable types (or both), (b) the account has a balance due which is above the obligatory minimum repayment,

(c) the account does not show a balance transfer to another credit card account[1]. After applying these sample restrictions, we focus our analysis on samples of the data in which the relationship between spending and repayment can be most cleanly analyzed. We used two main samples.

The first sample includes only the first month of data for new credit card accounts, in which all the spending is in either durable purchases or non-durable purchases. This is the cleanest sample for our analysis as the sample exhibits no prior history of spending or repayment behaviour and accounts can be cleanly separated by spending type. We use a dummy variable to label observations as either durable-spend or non-durable-spend months. We call this sample the *Single-Purchase-Type Sample*, which provides 21,671 month observations.

The second sample also restricts data to only the first month for new credit card accounts, but includes months in which the account incurs durable and non-durable spends in addition to the single purchase type months (hence, this sample includes the first sample above). For this sample we calculate the share of spending on durable purchases and the share of spending on non-durable purchases (which together sum to 1). We term this the *Multiple-Purchase-Type Sample*, which includes 58,404 month observations. Summary data for spending incurred in the first and second samples are shown in Tables 3.1 and 3.2.

In additional analysis, we extend the sample to include all months, not just the first month. Hence, we construct Single-Purchase-Type and Multiple-Purchase-Type samples which include repeated observations from the same account. Theses samples include accounts for which we have records of between a single month to many years. This substantially increases the sample size, with 154,000 observations of single purchase type months and 130,000 observations of multiple purchase type months. However, this represents a less clean sample for analysis as these accounts have histories of spending and repayment that may decouple mental accounts on the part of the cardholder (i.e., people may

[1]Specifically, under restriction (a) we remove month observations in which the account holder makes no transactions, withdraws cash using his/her card, pays utility bills or undertakes a classification unclassified in the merchant code data. These transactions fall outside of the mental accounting framework we consider here. Under restriction (b) we also excluded all months with total purchase amount lower than £5 during the preceding month, as balances equal to or less than this quantity need to be repaid in full, due to the required minimum policy. Ignoring such transactions is not problematic if small, routine expenses, such as coffee or lunch, are habitually not booked, emulating the organizational practice of allocating small expenditures to a petty cash fund that is not under scrutiny (Thaler, 1999). Under restriction (c) we also excluded months in which a balance transfer occurred on the account, as balance transfers reflect substitution of debts to other credit cards. We also excluded months in which repayments were made automatically by direct debit.

no longer be able to remember what they spent the money on when they are repaying their bill). Summary data for spending incurred in these samples are shown in Tables B.1.1 and B.1.2 of Appendix B.

Apart from differing in the number of observations, the four samples we draw show some differences in the level and composition of spends. The monthly spend on the new accounts single purchase type sample is lower compared to the new accounts multiple purchase type sample (£660 vs £745), a difference also see in the sample of all accounts in Tables B.1.1 and B.1.2 (£320 vs £420). The non-durable spending category with the highest mean spend, travel agencies, is the same across single and multiple samples (for new and all accounts), while in the multiple purchase type sample mean spending on airlines is notably higher.[2] In each sample, spending on durables is broadly spread across categories. As we show in Table 3.3, the socio-economic characteristics of card holders who contribute observations to each sample are very similar across samples.

3.3.4 Census Data Socio-Economic Controls

The data include geocodes, allowing us to match in socio-economic controls from the UK National Census Records. The data is geocoded at the 4-digit UK postcode level.[3] We match the following variables: (a) the median house price within the locality based on self-reported evaluations of selling prices, (b) self-reported median net weekly income, (c) the proportion of households within the locality with children enrolled in education who receive free school meal vouchers. The final measure is commonly used in the UK as an indication of social insurance dependency. Due to some missing postcodes within the credit card dataset, in the Single-Purchase-Type Sample we can match 70% of months to census records (107,384 of 154,924 months); and in the Multiple-Purchase-Type Sample, 69% (194,214 of 282,997 months). The addition of these variables to the dataset allows us to partially control for differences in credit card repayment arising from differences in socio-economic characteristics.

[2] This might be as expected if holiday purchases made via travel agents commonly occur in the same cycle as purchases of airline tickets to holiday destinations.

[3] There are approximately 3,000 UK 4-digit postcodes, which each contain on average 9,000 individual addresses, or 0.03% of all UK addresses.

Table 3.1 Descriptive Statistics for Purchase Amounts for the First Purchase for new Accounts – Single-Purchase-Type Sample

Merchant Category	Frequency	Mean	SD	p25	p50	p75
Non-durables						
Airlines	601	£931.12	£1,119.47	£208.75	£547.06	£1,194.87
Auto Rental	258	£263.60	£411.43	£73.29	£140.69	£286.90
Hotel/Motel	754	£526.41	£895.42	£90.00	£220.14	£500.00
Restaurants/Bars	632	£233.44	£821.13	£24.65	£49.65	£95.40
Travel Agencies	1885	£1,450.72	£1,224.57	£511.91	£1,140.87	£2,040.00
Other Transportation	561	£485.63	£1,059.86	£40.90	£100.00	£322.77
Drug Stores	125	£63.73	£173.20	£15.75	£25.00	£51.57
Gas Stations	1331	£90.35	£245.46	£34.46	£51.00	£80.08
Mail Orders	465	£230.69	£419.24	£29.50	£71.80	£235.31
Food Stores	2450	£113.14	£295.09	£23.59	£54.32	£112.56
Other Retail	1897	£457.90	£1,052.26	£29.99	£79.99	£363.00
Recreation	771	£422.19	£771.18	£65.00	£150.00	£405.60
Subtotal	11730	£501.78	£957.17	£40.05	£102.27	£466.00
Durables						
Department Stores	485	£458.81	£921.34	£55.79	£142.82	£458.32
Discount Stores	294	£191.40	£243.60	£44.99	£119.98	£263.93
Clothing Stores	1433	£170.40	£317.94	£37.00	£71.98	£150.00
Hardware Stores	687	£1,017.68	£1,594.09	£72.06	£331.56	£1,230.90
Vehicles	1200	£2,080.72	£2,282.94	£299.98	£1,100.00	£3,184.50
Interior Furnishing Stores	783	£1,113.82	£1,528.05	£234.00	£575.00	£1,248.45
Electric Appliance Stores	1028	£660.03	£811.64	£196.49	£419.99	£855.75
Sporting Goods/Toy Stores	510	£471.72	£784.74	£56.00	£155.34	£499.46
Health Care	414	£1,237.53	£1,573.06	£150.00	£414.50	£2,000.00
Education	191	£1,283.57	£1,640.86	£168.00	£775.00	£1,700.00
Professional Services	1257	£672.93	£852.91	£179.04	£410.00	£825.30
Repair Shops	16	£1,019.63	£1,273.31	£97.05	£491.39	£1,388.14
Other Services	1643	£831.82	£1,485.23	£60.50	£222.50	£947.12
Subtotal	9941	£854.70	£1,435.33	£81.41	£290.64	£931.25
Single purchase total	21671	£663.67	£1,213.18	£50.99	£167.95	£687.76

Note. Single purchase total shows the monthly spending for the Single-Purchase-Type Sample of monthly observations belonging to new credit card accounts. SD=standard deviation. p25=25th percentile, p50=median, and p75=75th percentile.

Table 3.2 Descriptive Statistics for Purchase Amounts for the First Purchase for New Accounts – Multiple-Purchase-Type Sample

	Frequency	Mean	SD	p25	p50	p75
Non-durables						
Airlines	2559	£1,176.40	£1,106.75	£412.81	£850.90	£1,571.49
Auto Rental	1138	£917.37	£1,082.72	£215.78	£540.18	£1,183.42
Hotel/Motel	5282	£959.71	£992.49	£311.00	£652.96	£1,257.84
Restaurants/Bars	12572	£796.63	£890.66	£237.12	£525.02	£1,025.39
Travel Agencies	4982	£1,445.37	£1,193.59	£563.55	£1,127.27	£1,973.36
Other Transportation	5888	£835.91	£960.92	£219.61	£523.17	£1,092.10
Drug Stores	4954	£834.38	£861.93	£275.70	£583.23	£1,084.79
Gas Stations	14894	£735.42	£853.47	£201.51	£470.37	£941.65
Mail Orders	3812	£807.45	£889.52	£218.38	£544.95	£1,066.45
Food Stores	23087	£668.35	£821.68	£166.94	£408.22	£849.35
Other Retail	16867	£806.69	£950.35	£216.22	£513.00	£1,030.25
Recreation	6394	£866.70	£910.35	£272.23	£591.46	£1,133.69
Subtotal	45304	£689.94	£930.20	£129.02	£365.98	£867.72
Durables						
Department Stores	6084	£919.96	£974.92	£295.14	£624.05	£1,170.77
Discount Stores	4052	£821.51	£841.83	£286.94	£581.33	£1,052.89
Clothing Stores	14563	£742.01	£822.92	£206.72	£485.90	£964.81
Hardware Stores	7124	£1,109.67	£1,197.62	£341.06	£743.07	£1,408.39
Vehicles	4700	£1,481.26	£1,642.09	£412.14	£887.19	£1,959.05
Interior Furnishing Stores	5656	£1,228.85	£1,275.01	£413.24	£825.02	£1,557.05
Electric Appliance Stores	5887	£1,031.85	£1,059.91	£354.99	£700.93	£1,344.82
Sporting Goods/Toy Stores	5611	£864.47	£881.34	£275.52	£594.87	£1,129.82
Health Care	2332	£1,101.77	£1,190.37	£325.59	£679.67	£1,425.71
Education	866	£1,102.37	£1,181.63	£344.00	£793.01	£1,404.02
Professional Services	5617	£1,049.22	£1,091.03	£355.20	£725.98	£1,352.74
Repair Shops	236	£1,125.72	£1,123.40	£349.27	£844.68	£1,449.76
Other Services	11158	£988.92	£1,161.31	£275.02	£633.79	£1,236.14
Subtotal	39685	£848.82	£1,117.68	£199.64	£477.17	£1,021.74
Multiple purchases total	58404	£735.09	£1,058.35	£122.85	£362.22	£893.76

Note. Multiple purchase total shows the monthly spending for the Multiple-Purchase-Type Sample of monthly observations belonging to new credit card accounts. Note that the Multiple-Purchase-Type Sample includes the Single-Purchase-Type Sample described in Table 3.1. As cardholders can consume products in more than one category during the month, frequencies for each category do not add to the month observations displayed in the multiple purchases total. SD=standard deviation. p25=25th percentile, p50=median, and p75=75th percentile.

3.3.5 Summary Statistics

Summary data for spending amounts in each of the 25 categories in the first month Single-Purchase-Type Sample are shown in Table 3.1. The sample comprises 21,671 observations. For non-durable spending the most common purchase category is 'food stores', for durable spending the most common purchase category is 'clothing stores'. Mean spending totals approximately £664 with median spending of £168. Table 3.2 shows the summary statistics for purchases in the Multiple-Purchase-Type Sample. Summary statistics for Single-Purchase-Type and Multiple-Purchase-Type samples including all accounts (not just new accounts) are shown in Tables A-1 and A-2 of Appendix A. Table 3.3 summarizes the socioeconomic variables for the four samples (New Accounts Single-Purchase-Type; New Accounts Multiple-Purchase-Type; All Accounts Single-Purchase-Type; All Accounts Multiple-Purchase-Type). The summary statistics are very similar across these samples.[4]

[4]This suggests that our four samples are very similar in terms of average socioeconomic cardholder characteristics. However, we are only able to match socioeconomic variables based on postcode for 68% of the cardholders in the data.

Table 3.3 Descriptive Statistics of Cardholders' Socioeconomic Characteristics for the Samples Under Study

	Number of Cardholders	Number of Accounts	Mean	SD	p25	p50	p75
New accounts							
Single-Purchase-Type Sample							
Median house price (£)	14,766	14,851	£203,261.50	£103,940.20	£133,622.90	£182,269.40	£241,094.10
Free school meals (%)	14,766	14,851	12.97%	7.01%	7.83%	11.57%	16.68%
Weekly Household Income (£)	14,766	14,851	£742.29	£155.42	£626.54	£719.58	£837.01
New accounts							
Multiple-Purchase-Type Sample							
Median house price (£)	38,010	38,481	£206,902.10	£105,695.60	£135,989.00	£185,029.90	£244,892.20
Free school meals (%)	38,010	38,481	12.77%	6.98%	7.65%	11.44%	16.52%
Weekly Household Income (£)	38,010	38,481	£749.99	£156.83	£631.34	£726.35	£847.48
All accounts							
Single-Purchase-Type Sample							
Median house price (£)	64,478	66,021	£204,339.10	£105,353.00	£135,034.20	£184,025.80	£241,339.10
Free school meals (%)	64,478	66,021	12.35%	6.72%	7.44%	11.01%	15.82%
Weekly Household Income (£)	64,478	66,021	£746.44	£155.47	£630.00	£721.99	£839.18
All accounts							
Multiple-Purchase-Type Sample							
Median house price (£)	104,643	108,050	£207,050.30	£107,419.00	£136,933.60	£185,437.60	£243,501.40
Free school meals (%)	104,643	108,050	12.34%	6.77%	7.39%	11.00%	15.84%
Weekly Household Income (£)	104,643	108,050	£750.68	£156.74	£631.78	£725.22	£846.84

Note. Socioeconomic data were obtained by matching cardholders' postcodes to the UK National Census Records. Data matched includes: the median house price within the locality based on self-reported evaluations of selling prices, self-reported median net weekly income, and the proportion of households within the locality with children enrolled in education who receive free school meal vouchers. Due to some missing postcodes within the credit card dataset, descriptive statistics in the table correspond to 68% of the total number of cardholders in the dataset whose month observations met the selection criteria imposed. SD=standard deviation. p25=25th percentile, p50=median, and p75=75th percentile.

3.3.6 Econometric Model

Our main interest lies in estimating whether the propensity of credit cardholders to repay a credit card bill incurred in a given month relates to the type of purchases made in that month.

We begin by estimating the following baseline model:

$$
\begin{aligned}
P(Repay_{it} = 1) = \beta_0 + \beta_1 NonDurable_{it} + \beta_2 APR_{it} + \beta_3 CreditLimit_{it} \\
+ \beta_4 Tenure_{it} + \beta_5 Utilization_{it} + \sum_f \phi_f X_{fit}
\end{aligned}
\quad (3.1)
$$

where *Repay* is a 1/0 dummy variable which takes a value of 1 if at least 90% of the bill is repaid within the following month (the period in which payment of the bill becomes due). We used the 90% threshold to take into account the possibility of people paying the bill by rounding down to the nearest tenth or hundred and failing to pay the exact amount, though our analysis is robust to variations in this arbitrary choice. The variable $NonDurable$ describes the purchases made on the account. In estimates based on the Single-Purchase-Type Sample, this variable is a 1/0 dummy variable taking a value of 1 if the month contains non-durable purchases and a value of 0 for durable purchases. In the Multiple-Purchase-Type Sample, this variable is the proportion of purchases (as a proportion of the total monthly spend) on non-durables.

The additional variables in the model which act as control variables (all measured at the month level) are: the annualized percentage rate on card purchases (APR), the credit limit on the credit card account ($CreditLimit$), the age of the account in years ($Tenure$) and a measure of utilization ($Utilization$). Account utilization is measured as the ratio of the account balance (before repayment is made) over the credit limit. Hence, a utilization value of 0.5 indicates a balance on the account at a value of half the credit limit.

The model also includes additional controls (captured by the vector X in Equation 3.1): calendar month fixed effects to control for seasonal differences in patterns of spending and repayment (for example, the months of November and December are more likely to include purchases of seasonal gifts). The vector also includes the socio-economic control variables, which are measured at the geocode level (which contains a cluster of account $\times$ months). We also add to the model controls for the value of the credit card bill. These are important controls, as due to the lumpiness of durable purchases, accounts with durable purchases typically have higher total purchases than those with non-durable purchases and hence these accounts might naturally have a lower likelihood of being repaid in full. As a first approach, we control for the total purchase amount, allowing for a flexible relationship between purchase amount and the probability of repayment using a fifth-order polynomial. As a second approach, we split the sample into quartiles of the total amount of durable purchases and estimate models on each quartile on observations separately, while continuing to include the fifth order polynomial of the total purchase amount as controls in the model.[5]

We estimate our main models as Linear Probability Models (LPMs). We also present estimates based upon Random Effects (RE) models and Fixed Effects (FE) models. These account for correlations among repeated measures of the same credit card account holder within the dataset.

3.4 Results

3.4.1 Single Purchase Type Sample

Results from our main model estimates of Equation 3.1 for the Single-Purchase-Type Sample are shown in Table 3.4. Column 1 shows estimates from a model which includes only a 1/0 dummy variable indicating whether purchases in the month were non-durable and a constant term. Hence the reference group is months of account data which contain durable purchases only. The coefficient on the non-durable purchase dummy is 0.197, 95% CI [0.184, 0.210], and indicates that people are almost an absolute 20 percentage points more likely to pay their bill in full when the bill comprises monies spent on non-durable purchases. Columns 2 and 3 add the controls for the fifth-order polynomial in purchase amount, calendar month fixed effects and card characteristics. As expected, with the addition of controls for the purchase amount in Column 2, the R-squared of the model increases substantially and the coefficient on the non-durable dummy variable reduces in absolute magnitude. The coefficient on the non-durable dummy is 0.097, 95% CI [0.084, 0.106], and indicates that people are almost an absolute 10 percentage points more likely to pay their bill in full when the bill comprises monies spent on non-durable purchases.

[5]We split the sample by quartiles of the total value of durable purchases, instead of splitting the sample by the total value of all purchases, in order to avoid generating quartiles which contain account x month observations with nearly all observations of durable purchases only or non-durable purchases only.

Table 3.4 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1	OLS – Quartile 2	OLS – Quartile 3	OLS – Quartile 4
				(£5.02 - £81.41)	(Q2: £81.42 - £290.64)	(Q3: £290.65 - £931.25)	(£931.26 - £17000)
Non-durable = 1	0.197***	0.0966***	0.0955***	0.0422***	0.139***	0.0992***	0.0372***
	(0.00667)	(0.00571)	(0.00564)	(0.00883)	(0.0131)	(0.0139)	(0.00918)
Merchant APR (%)			0.00615***	0.00326***	0.00730***	0.00837***	0.00893***
			(0.000343)	(0.000471)	(0.000791)	(0.000894)	(0.000750)
Credit limit (£1000)			0.00242*	-0.000805	0.00740**	0.00255	0.000143
			(0.00129)	(0.00195)	(0.00304)	(0.00371)	(0.00367)
Utilization (%)			-0.00152***	-0.00723***	-0.00176*	-0.00229***	-0.000782**
			(0.000217)	(0.00222)	(0.00102)	(0.000449)	(0.000352)
Account age (years)			0.126***	0.00449	0.162***	0.281***	0.298***
			(0.0123)	(0.0167)	(0.0289)	(0.0310)	(0.0263)
Amount purchase (£1000)		-1.036***	-0.919***	29.37**	9.604	-56.08*	-0.264***
		(0.0163)	(0.0197)	(13.21)	(61.99)	(29.39)	(0.0629)
Amount purchase $(£1000)^2$		0.459***	0.419***	-1,619*	-93.55	198.2*	0.0907***
		(0.0114)	(0.0118)	(843.0)	(755.9)	(107.8)	(0.0264)
Amount purchase $(£1000)^3$		-0.0821***	-0.0756***	38,230	291.3	-339.2*	-0.0136***
		(0.00273)	(0.00274)	(23,613)	(4,430)	(191.3)	(0.00468)
Amount purchase $(£1000)^4$		0.00619***	0.00571***	-421,664	-97.45	280.1*	0.000904**
		(0.000252)	(0.000251)	(298,838)	(12,515)	(164.5)	(0.000358)
Amount purchase $(£1000)^5$		-0.000162***	-0.000150***	1.752×10^{6}	-601.2	-89.57	-2.19×10^{-5}***
		(7.67×10^{-6})	(7.62×10^{-6})	(1.396×10^{6})	(13,677)	(54.90)	(9.63×10^{-6})
Constant	0.421***	0.759***	0.681***	0.659***	0.264	6.413**	0.287***
	(0.00491)	(0.00557)	(0.0160)	(0.0744)	(1.951)	(3.093)	(0.0559)
Observations	21,671	21,671	21,671	7,676	5,317	4,223	4,455
Observations Non-durable = 1	11,730	11,730	11,730	5,191	2,832	1,737	1,970
R-squared	0.039	0.325	0.344	0.033	0.077	0.100	0.106
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. The sample is restricted to new accounts and includes months in which purchases were related to only one merchant code (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

To gauge the quantitative importance of the coefficient estimates, Figure 3.2 plots the predicted probability of repayment from the model estimates in Table 3.4 (Column 3). The circles indicate the predicted probability and bars indicate 95% confidence intervals. In the top panel, the whole sample bars show that non-durable spending type months have a predicted probability of repayment of approximately 60%, compared with approximately 50% for accounts in the durable category. This 10-percentage-point difference is large in economic terms. A natural economic comparison is to the increase in APR which would generate an equivalent increase in the predicted probability of bill repayment. We make this comparison based on the estimated coefficient on the APR variable in the model, which allows us to make a correlational comparison.[6] Using the estimates from Column 3 of Table 3.4, a 15-percentage-point increase in APR would be needed to deliver the equivalent increase in likelihood of card repayment.

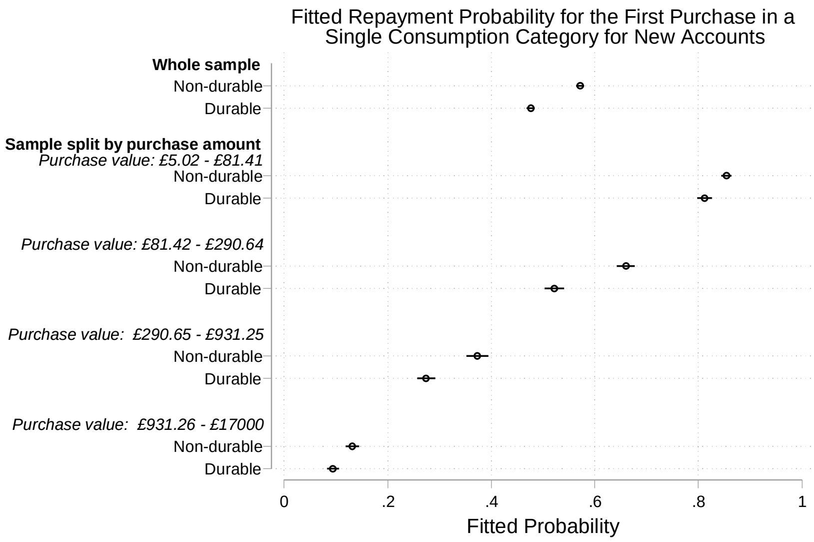


Fig. 3.2 Probabilities of full repayment – single consumption category. Fitted probabilities of full repayment based on linear probability models (see Table 3.4, Columns 3 to 7), evaluated at the mean of the other covariates. Lines span 95% confidence intervals.

The lower part of Figure 3.2 breaks down the predictions by quartiles of purchase value. Coefficient estimates are shown in Columns 4–7 of Table 3.4. Across the quartiles, the predicted probability of repayment is higher for spends

[6] One caveat to this exercise is that in our data we do not have random variation in APR. For studies exploiting quasi-experimental variation in APR or random variation, see Alan and Loranth (2013); Bertrand et al. (2010); Gross and Souleles (2002).

on non-durable goods, with the difference in predicted probability ranging from approximately 0.04 to 0.14.

Table B.2.1 in the Appendix B.2 shows results with the addition of socio-economic controls. The coefficients on the non-durable dummy variable are very similar to those in Table 3.4.

3.4.2 Multiple Purchase Type Sample

Table 3.5 shows results from the main model estimates of Equation 3.1 for the multiple purchase type sample. In these models the non-durable variable measures the proportion of the spend in the month that are of the non-durable type. The coefficient for the non-durable variable is 0.239, 95% CI [0.229, 0.249], and implies that as the share of non-durable purchases increases from zero to 100%, people are almost exactly an absolute 24 percentage points more likely to pay their bill in full for non-durable purchases. As in the estimates in Table 3.4, with the inclusion of controls in Columns 2 and 3, the value of this coefficient falls in magnitude. The coefficient value of 0.149, 95% CI [0.140, 0.158], in Column 3, indicates that a switch in the proportion of the total monthly spending in the non-durable category from 0% to 100% increases the likelihood of full repayment by almost exactly 15 percentage points. Again, this is a large effect in economic terms. Using the coefficient estimates in Column 3, the effect of switching spending on non-durable purchases from 0% to 100% is equivalent to a 21-percentage-point increase in the card APR. Figure 3.3 shows the size of the difference of the predicted probability of repayments of durable and non-durable purchases.

The pattern of coefficient estimates on the control variables resembles that in Table 3.4 The likelihood of full repayment of the credit card bill is increasing with the APR and credit limit, but falling with account utilization. Columns 4 to 7 of Table 3.5 present estimates by quartile sub-samples. As before, the coefficients on the non-durable variable are positive and precisely defined in each specification, with the coefficient values implying an increase in the likelihood of repayment of between 5 and 22 percentage points from a switch in the proportion of the spend in non-durable purchases from 0 to 1. Table B.2.2 in the Appendix C.2 presents estimates from the same set of models as Table 3.5 with the inclusion of socio-economic control variables. The pattern in the coefficient estimates is as before.

Table 3.5 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1	OLS – Quartile 2	OLS – Quartile 3	OLS – Quartile 4
				(£5.02 - £81.41)	(Q2: £81.42 - £290.64)	(Q3: £290.65 - £931.25)	(£931.26 - £17000)
Non-durable (proportion)	0.239***	0.152***	0.149***	0.0454***	0.171***	0.219***	0.105***
	(0.00488)	(0.00448)	(0.00441)	(0.00820)	(0.00946)	(0.00883)	(0.00762)
Merchant APR (%)			0.00697***	0.00372***	0.00684***	0.00787***	0.00878***
			(0.000249)	(0.000411)	(0.000480)	(0.000520)	(0.000618)
Credit limit (£1000)			0.00745***	0.00128	0.0102***	0.0123***	0.00786***
			(0.000914)	(0.00173)	(0.00188)	(0.00185)	(0.00233)
Utilization (%)			-0.00199***	-0.00530***	-0.00163***	-0.00185***	-0.00136***
			(0.000140)	(0.00175)	(0.000538)	(0.000244)	(0.000245)
Account age (years)			0.143***	0.0150	0.139***	0.217***	0.259***
			(0.00976)	(0.0149)	(0.0195)	(0.0207)	(0.0231)
Amount purchase (£1000)		-0.855***	-0.696***	21.00*	68.64*	2.353	-0.183***
		(0.0111)	(0.0132)	(12.15)	(37.90)	(14.58)	(0.0495)
Amount purchase $(£1000)^2$		0.389***	0.325***	-1,076	-844.2*	-7.114	0.0500**
		(0.00820)	(0.00839)	(759.2)	(457.5)	(53.25)	(0.0221)
Amount purchase $(£1000)^3$		-0.0730***	-0.0613***	23,187	4,913*	7.491	-0.00645
		(0.00207)	(0.00208)	(20,873)	(2,656)	(94.05)	(0.00413)
Amount purchase $(£1000)^4$		0.00577***	0.00485***	-235,712	-13,768*	-2.133	0.000403
		(0.000201)	(0.000200)	(259,915)	(7,438)	(80.48)	(0.000330)
Amount purchase $(£1000)^5$		-0.000158***	-0.000133***	912,643	14,925*	-0.484	$-9.71x10^{-6}$
		$(6.36x10^{-6})$	$(6.31x10^{-6})$	$(1.197x10^{6})$	(8,063)	(26.76)	$(9.21x10^{-6})$
Constant	0.334***	0.682***	0.568***	0.691***	-1.638	0.00857	0.259***
	(0.00341)	(0.00446)	(0.0107)	(0.0694)	(1.205)	(1.541)	(0.0411)
Observations	58,404	58,404	58,404	10,585	15,185	18,672	13,962
R-squared	0.040	0.219	0.245	0.033	0.063	0.087	0.084
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table 3.5 replicates Table 3.4 specifications for the sample in which months with both consumption types are included in the sample. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

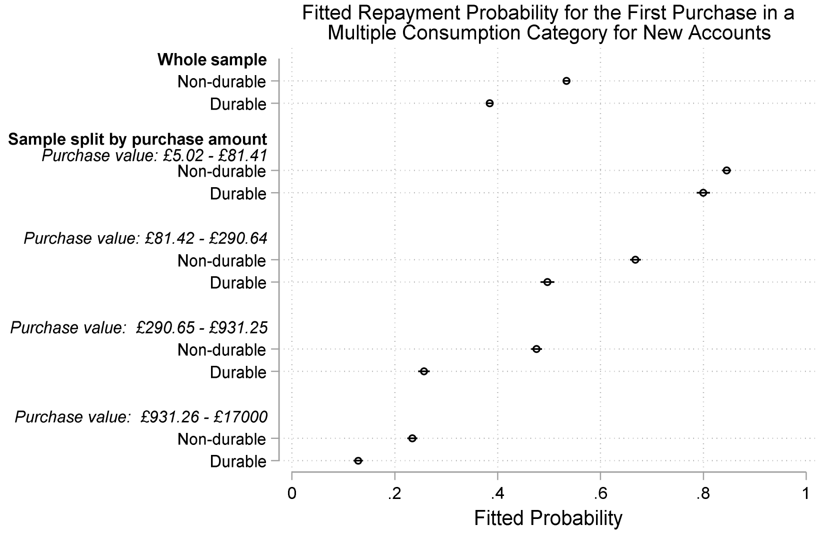


Fig. 3.3 Probabilities of full repayment – multiple consumption category. Fitted probabilities for full repayment based on linear probability models (see Table 3.5, Columns 3 to 7), evaluated at the mean of the other covariates. Lines span 95% confidence intervals.

3.4.3 Alternative Classification of Purchase Categories

To test whether our results depend on the classification of purchases used, we perform two additional robustness tests. First, as discussed above, some purchase categories might contain both durable and non-durable items. Therefore, we re-estimate the main results re-classifying these items in to the opposite purchase type. Specifically, we flip the classification of the following categories: from non-durable to durable, other retail; and from durable to non-durable, professional services, other services, and discount stores. Appendix B.3 replicates the main results (Tables B.3.1 and B.3.4) for this alternative classification. Our findings remain consistent with the main results.

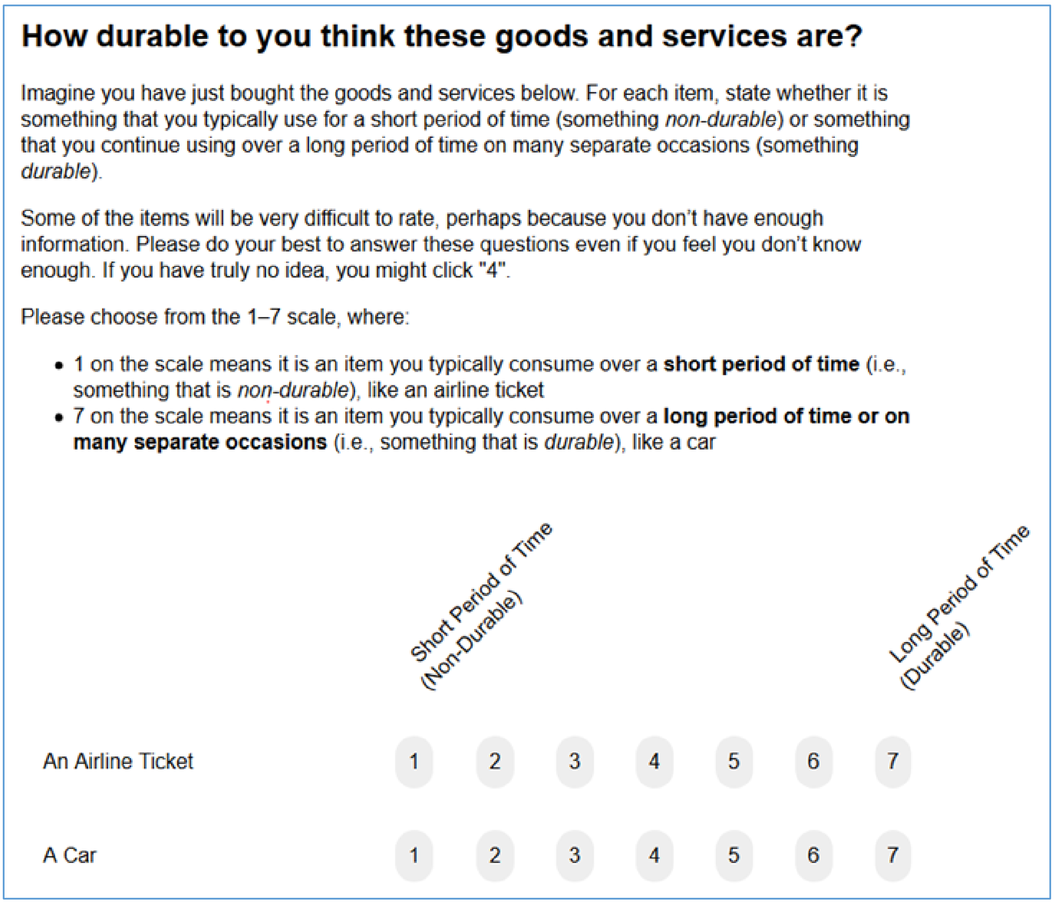
Second, although our sample does not contain business credit cards, it is possible that some card holders use a personal credit card for business expenses. Such expenditure is likely to be non-durable spending which are reimbursed by the card holder's employer and hence are likely to be repaid quickly. To control for this, we re-estimated the main models omitting the following categories which are those most likely to contain business expense: hotel / motel, travel agencies, airlines, other transportation. Appendix B.4 replicates the main results (Tables B.4.1–B.4.6). Our findings remain consistent with the main results.

We also estimate models using the underlying merchant codes which are classified into durable and non-durable expenditure. Appendix B.5 (Tables B.5.1–B.5.4) shows the estimated marginal effects for each individual merchant code. The size of these effects can be observed in Figures 3.5 and 3.6. Figure 3.5 displays the probability of full repayment of each non-durable merchant code and, as a point of comparison at the bottom of the figure, the probability of full repayment over all durable expenditures. Figure 3.5 shows that every non-durable expenditure is more likely to be repaid in full than the average over all durable expenditures. Figure 3.6 displays the probability of full repayment of each durable merchant code and, as a point of comparison at the bottom of the figure, the probability of full repayment over all non-durable expenditures. Figure 3.6 shows that every durable expenditure is less likely to be repaid in full than the average over all non-durable expenditures. Hence, our main result that individuals are less likely to pay down durable spending is not driven by only a few categories.

3.4.4 Using Durability Measures from a Consumer Survey

As an alternative approach to classifying items as durable and non-durable we undertook a consumer survey on the platform Prolific Academic in which 501 individuals recruited were asked to rate the durability of items on a 1–7 scale. We obtained from Argus the approximately 500 next-level-down items that feed into the 25 categories used in the analyses above, and asked survey respondents to rate the durability of these individual items. Several of the items received from Argus made reference to company names (for instance, for the merchant code "airlines" we have American Airlines, British Airways, Japan Airlines, etc.). There were 126 airlines companies, 80 hotels, and 24 auto rental companies. After aggregating such items, we ended up with 274 items to test. However, some of these items were exceptionally rare with purchase frequencies of less than 1 in 1000 in the National Accounts. After excluding these rare cases, we retained and tested 152 items. These 152 categories cover 95% of the weights used in the 2014 UK Consumer Price Inflation indices. We used the following question format:

We gave each of 501 respondents recruited from Prolific Academic (and restricted to UK nationals living in the UK) a list of these 152 of these 500 next-level-down spending categories (e.g., "An Airline Ticket") and had them



How durable to you think these goods and services are?

Imagine you have just bought the goods and services below. For each item, state whether it is something that you typically use for a short period of time (something *non-durable*) or something that you continue using over a long period of time on many separate occasions (something *durable*).

Some of the items will be very difficult to rate, perhaps because you don't have enough information. Please do your best to answer these questions even if you feel you don't know enough. If you have truly no idea, you might click "4".

Please choose from the 1–7 scale, where:

- 1 on the scale means it is an item you typically consume over a **short period of time** (i.e., something that is *non-durable*), like an airline ticket
- 7 on the scale means it is an item you typically consume over a **long period of time or on many separate occasions** (i.e., something that is *durable*), like a car

	Short Period of Time (Non-Durable)					Long Period of Time (Durable)
An Airline Ticket	1	2	3	4	5	6	7
A Car	1	2	3	4	5	6	7

Fig. 3.4 Question format used in the consumer survey for the classification of items in durables and non-durables.

evaluate the degree to which the item was a durable or non-durable. Some few people did not provide scores to some items in the survey because they were not required to evaluate all items if they did not want to. But 500 people replied at least 95% of the survey items. From these responses we calculated weighted average durability scores for the 25 merchant categories, applying expenditure weights from the UK National Accounts and reclassified the 25 merchant categories as durable or non-durable items. Our survey design and steps in analysis were pre-registered, with details of the methods (https://aspredicted.org/f9iu4.pdf) and results shown in Appendix B.7.

The durable/non-durable classification from the consumer survey was very close to the original classification based on Kuchler (2013), with the exceptions being 'health care', 'professional services', 'other services', 'mail orders' and 'other retail'. To test the sensitivity of our results, we re-estimated the main models using durability scores from the survey responses. The regression tables in Appendix B.7 are in keeping with our earlier analysis for both the single purchase type and multiple purchase samples.

3.4.5 Controlling for Characteristics of Other Cards

We also test whether our results are robust to controlling for balances due on other cards held by the individual at the same time. Drawing from the same universe of data, Gathergood et al. (2017) show that consumers tend adopt a repayment heuristic when making intra-temporal choices over allocating payments across cards due within the same month. Instead of paying down the highest interest rate debt first, as economic logic would predict, consumers tend to split the ratio of repayments across their cards in approximate proportion to the ratio of revolving balances, which Gathergood et al. (2017) describe as the application of a 'balance-matching heuristic'.

We draw the sub-sample of observations from our main sample in which individuals hold two or more cards concurrently within the same month with positive balances due.[7] The resulting sample differs from that used in Gathergood et al. (2017), who design their analysis to focus on partial repayment of revolving debts, restricting to cases where consumer face interest payments, in

[7]Our universe of data contains records from five UK credit card issuers. While these issuers comprise more than 40% of the UK market by number of cards, we cannot see all cards held by all individuals in our sample. Therefore, we necessarily restrict our sample by more than if we had data on all cards in the UK.

contrast to our focus on full repayment.[8]We first replicate our main models on this sample (without adding controls for additional cards), for completeness including socio-economic controls in the regression specification. Appendix B.6 Table B.6.1 shows that the coefficients on the non-durable variables are very similar to those obtained using the main samples.

In Tables B.6.2 to B.6.5 we then expand the econometric specification by adding control variables drawing on characteristics of the other cards held. We first control for the number of cards held. In a series of additional models, we then control for the balance on other cards, the ratio of the balance of the first card to the total balance on all cards (to control for 'balance-matching' across cards), and additional specifications including dummy variables for whether the first card has the highest utilization among all cards, lowest utilization among all cards, highest balance among all cards and finally the lowest balance among all cards. We do not include all of these measures in a single specification are they are highly correlated.[9]

Results show that the coefficients on the non-durable variables are unchanged from those in the earlier models. The coefficients on the multiple-card variables are consistent with consumers being more likely to pay down the card with the highest balance. The coefficient on the ratio of balance on the first card to balances on all cards is positive and statistically significant at the 1% level, implying a higher balance on the current card increases the likelihood of full repayment. The coefficients on the other variables show that when the first card has the highest balance, or utilization (which correlate), the card is more likely to be repaid in full, and conversely when the first card has the lowest

[8]Specifically, Gathergood et al. (2017) restrict their sample to observations where individuals, holding fixed total monthly repayments, have scope to reallocate payments across cards to minimize interest charges. They restrict the sample to months in which the individual i) carries revolving debt on all cards, ii) faces different interest rates on the cards, iii) pays at least the minimum balance due on all cards and iv) does not pay all their cards down in full. These restrictions allow the authors to analyse whether individuals are minimising their interest charges. In the current analysis, we restrict to observations where the individual begins the month not revolving any debt (so that we can link spending and repayment). Hence, the samples used in the current paper and those in Gathergood et al. (2017) are mutually exclusive.

[9]Gathergood et al. (2017) design analysis to distinguish which from a set of candidate repayment heuristics based on these variables best explain consumer repayment behaviour across multiple cards. They use two approaches, one based upon goodness of fit criterion to determine which heuristic is closest on average to the observed allocation of payments across cards and a second based on determining which heuristic best fits on an observation-by-observation basis. Our econometric implementation of these heuristics as control variables in Appendix B.6, while delivering results in keeping with those from Gathergood et al. (2017), does not therefore exactly match the econometric techniques used in that paper.

balance, or utilization, it is less likely to be repaid in full. From this analysis we conclude that repayment behaviour appears to be driven by both inter-temporal mental accounting and also the application of intra-temporal heuristics.

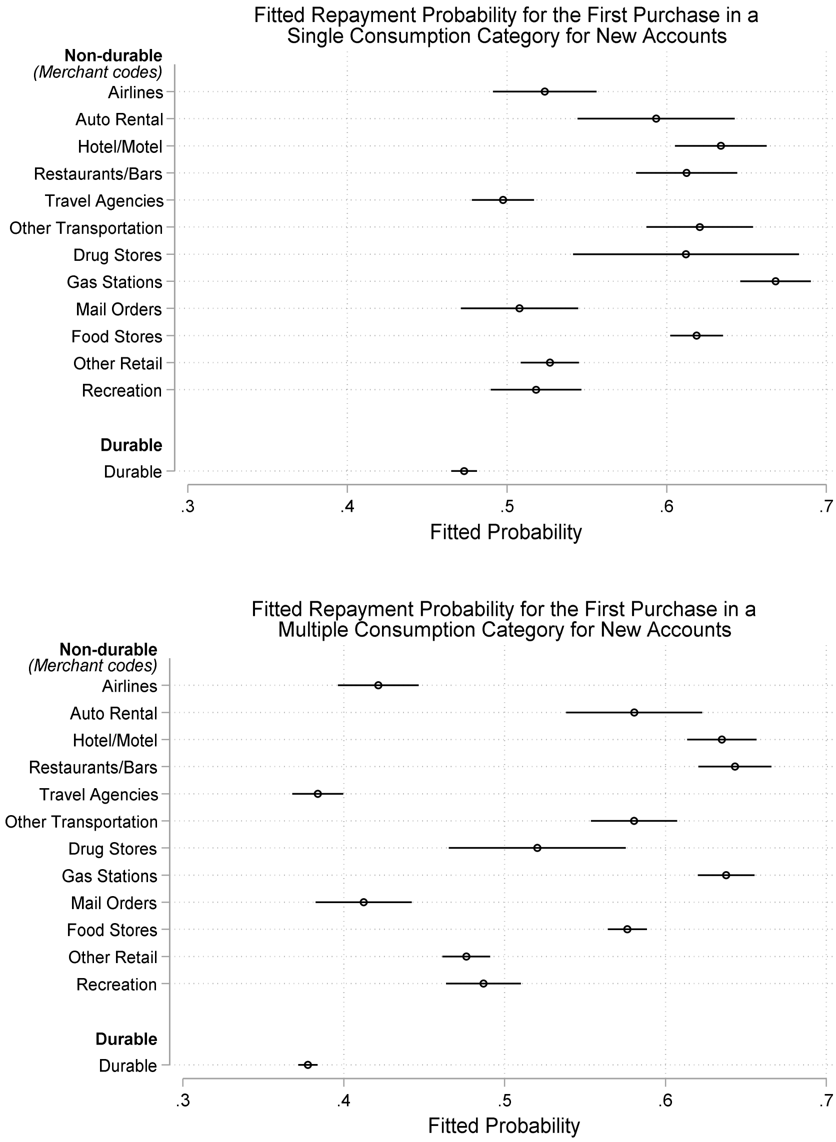


Fig. 3.5 Probabilities of full repayment by merchant codes – single consumption category. Fitted probabilities of full repayment based on linear probability models (see Tables B.5.1 and B.5.2, Column 1), evaluated at the mean of the other covariates. Lines span 95% confidence intervals

3.4.6 Older Accounts Samples

Next, we widened the sample to older accounts, incorporating months of data which include single and multiple purchase types. In these wider samples, we see multiple observations of the same account over different months. Therefore,

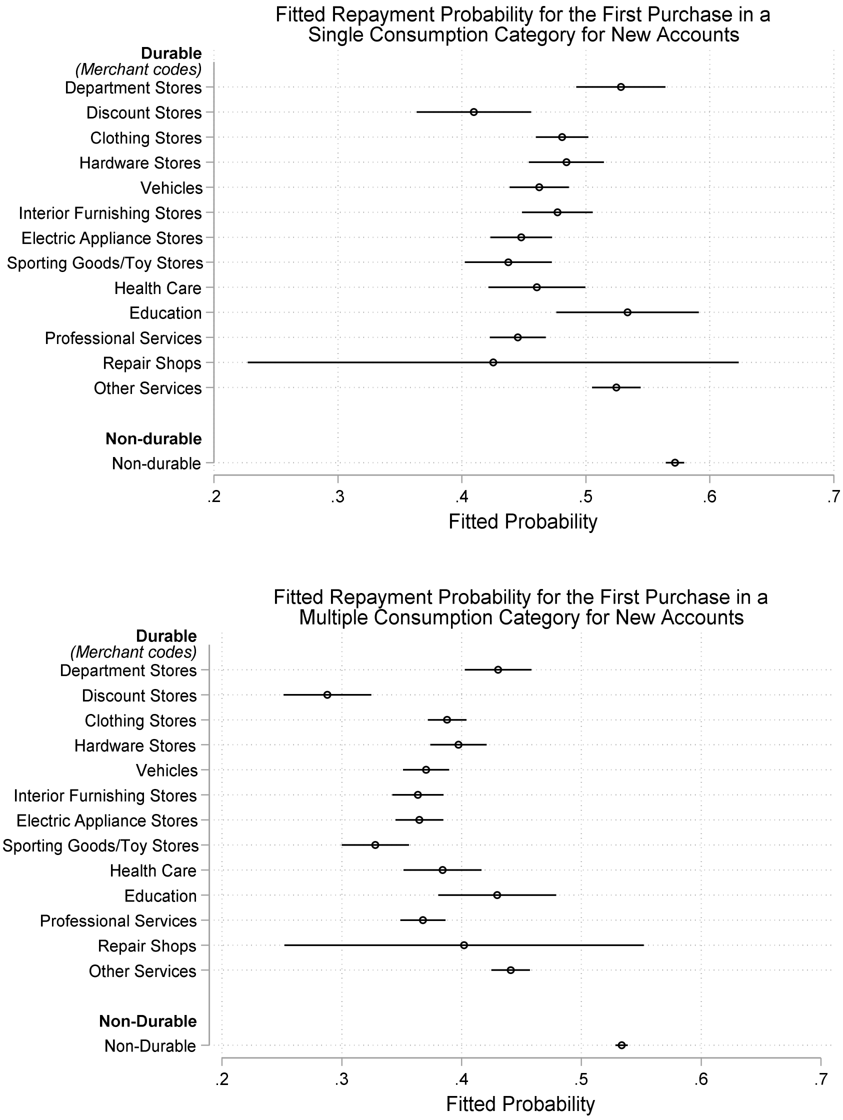


Fig. 3.6 Probabilities of full repayment by merchant codes – multiple consumption category. Fitted probabilities for full repayment based on linear probability models (see Tables B.5.3 and B.5.4, Column 1), evaluated at the mean of the other covariates. Lines span 95% confidence intervals.

we are able to estimate models with individual level random effects and fixed effects.

Table 3.6 shows results from a Single-Purchase-Type Sample of older accounts. We report specifications without controls (Column 1), with the inclusion of a fifth-order polynomial in purchase amount (Column 2) and with the inclusion of additional controls and month fixed effects (Column 3). Columns 4–6 repeat these three specifications with the addition of socio-economic controls. The sample size is smaller as these controls are available for only for 69% of the data. Columns 7–9 again repeat these specifications with the addition of individual fixed effects. The sample size reduces in these specifications as only accounts which contribute at least two months are retained in the account fixed effects models.

Results show that, consistently across all model estimates, the coefficient on the non-durable purchase type dummy is positive with a tight CI. Based upon the fullest specifications incorporating controls (Columns 3, 6 and 9), the coefficient on the non-durable dummy implies switching from durable to non-durable purchases raises the likelihood of repayment by between 0.7–3.0 percentage points, a smaller range of magnitude to that found in the earlier analysis of new accounts. The coefficient estimates on the covariates are keeping with those returned in previous models: the propensity to repay an account in full increases with APR and reduces with the credit limit and card utilization.

Table 3.7 reports results from the Multiple-Purchase-Type Sample. The sample is here again much larger due to the higher prevalence of accounts with purchase of more than one consumption type. Across all model estimates shown in Table 3.7, the coefficient on the proportion of the total monthly spending on purchases of the non-durable type is positive and precisely defined. Depending upon the model specification, the coefficient varies between 1.0–4.0 percentage points. Hence, the propensity to repay accounts in full increases with non-durable purchases among older accounts even when conditioning for account random and fixed effects.

Table 3.6 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable = 1	0.0403***	0.0243***	0.0249***	0.0383***	0.0223***	0.0230***	0.0116***	0.00717***	0.00708***
	(0.00162)	(0.00159)	(0.00156)	(0.00194)	(0.00191)	(0.00188)	(0.00201)	(0.00201)	(0.00201)
Merchant APR (%)			0.0103***			0.00875***			0.00280***
			(0.000153)			(0.000187)			(0.000372)
Credit limit (£1000)			-0.00285***			-0.00255***			0.00643*
			(0.000379)			(0.000444)			(0.00357)
Utilization (%)			-0.00323***			-0.00334***			-0.000726***
			(9.49×10^{-5})			(0.000115)			(0.000156)
Account age (years)			0.00484***			0.00461***			-0.0111***
			(0.000137)			(0.000155)			(0.00171)
Amount purchase (£1000)		-0.357***	-0.211***		-0.348***	-0.208***		-0.145***	-0.120***
		(0.00543)	(0.00640)		(0.00646)	(0.00766)		(0.00742)	(0.00927)
Amount purchase (£1000)^2		0.110***	0.0817***		0.107***	0.0792***		0.0555***	0.0503***
		(0.00380)	(0.00378)		(0.00447)	(0.00447)		(0.00539)	(0.00552)
Amount purchase (£1000)^3		-0.0153***	-0.0123***		-0.0146***	-0.0115***		-0.00875***	-0.00816***
		(0.000853)	(0.000833)		(0.000984)	(0.000969)		(0.00124)	(0.00125)
Amount purchase (£1000)^4		0.000937***	0.000776***		0.000859***	0.000698***		0.000555***	0.000525***
		(7.15×10^{-5})	(6.96×10^{-5})		(8.10×10^{-5})	(7.94×10^{-5})		(0.000107)	(0.000107)
Amount purchase (£1000)^5		-2.03×10^{-5}***	-1.71×10^{-5}***		-1.79×10^{-5}***	-1.48×10^{-5}***		-1.20×10^{-5}***	-1.15×10^{-5}***
		(1.96×10^{-6})	(1.90×10^{-6})		(2.18×10^{-6})	(2.13×10^{-6})		(2.99×10^{-6})	(2.99×10^{-6})
Median house price (£)				1.32×10^{-8}	7.37×10^{-9}	-1.04×10^{-9}			
				(2.30×10^{-8})	(2.14×10^{-8})	(2.05×10^{-8})			
Free school meals (%)				-0.306***	-0.276***	-0.194***			
				(0.0268)	(0.0250)	(0.0240)			
Weekly Household Income (£)				-2.44×10^{-5}	-8.17×10^{-6}	6.07×10^{-6}			
				(1.77×10^{-5})	(1.65×10^{-5})	(1.58×10^{-5})			
Constant	0.782***	0.870***	0.694***	0.844***	0.914***	0.738***			
	(0.00154)	(0.00172)	(0.00402)	(0.0124)	(0.0116)	(0.0119)			
R-squared							0.001	0.014	0.016
Observations	154,924	154,924	154,924	107,384	107,384	107,384	93,957	93,957	93,957
Number of accounts	95,461	95,461	95,461	66,021	66,021	66,021	34,494	34,494	34,494
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. The sample includes all accounts and includes months in which expenses were related to only one merchant code (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.7 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable (proportion)	0.0469***	0.0316***	0.0357***	0.0433***	0.0288***	0.0329***	0.0172***	0.0117***	0.0117***
	(0.00138)	(0.00137)	(0.00133)	(0.00165)	(0.00164)	(0.00160)	(0.00160)	(0.00159)	(0.00159)
Merchant APR (%)			0.0126***			0.0111***			0.00475***
			(0.000113)			(0.000137)			(0.000235)
Credit limit (£1000)			-0.00220***			-0.00236***			0.00957***
			(0.000335)			(0.000392)			(0.00236)
Utilization (%)			-0.00322***			-0.00328***			-0.000854***
			(6.69x10^{-5})			(8.18x10^{-5})			(0.000103)
Account age (years)			0.00659***			0.00628***			-0.00743***
			(0.000125)			(0.000140)			(0.00128)
Amount purchase (£1000)		-0.343***	-0.165***		-0.323***	-0.159***		-0.153***	-0.122***
		(0.00397)	(0.00459)		(0.00471)	(0.00550)		(0.00498)	(0.00613)
Amount purchase (£1000)^2		0.118***	0.0700***		0.107***	0.0647***		0.0630***	0.0560***
		(0.00292)	(0.00287)		(0.00341)	(0.00338)		(0.00380)	(0.00387)
Amount purchase (£1000)^3		-0.0181***	-0.0114***		-0.0159***	-0.0101***		-0.0109***	-0.0100***
		(0.000692)	(0.000669)		(0.000791)	(0.000772)		(0.000929)	(0.000933)
Amount purchase (£1000)^4		0.00121***	0.000780***		0.00102***	0.000658***		0.000763***	0.000708***
		(6.10x10^{-5})	(5.86x10^{-5})		(6.83x10^{-5})	(6.63x10^{-5})		(8.44x10^{-5})	(8.44x10^{-5})
Amount purchase (£1000)^5		-2.83x10^{-5}***	-1.84x10^{-5}***		-2.31x10^{-5}***	-1.50x10^{-5}***		-1.81x10^{-5}***	-1.69x10^{-5}***
		(1.73x10^{-6})	(1.66x10^{-6})		(1.91x10^{-6})	(1.84x10^{-6})		(2.48x10^{-6})	(2.48x10^{-6})
Median house price (£)				8.53x10^{-8}***	7.40x10^{-8}***	5.10x10^{-8}***			
				(1.96x10^{-8})	(1.83x10^{-8})	(1.71x10^{-8})			
Free school meals (%)				-0.365***	-0.356***	-0.228***			
				(0.0232)	(0.0216)	(0.0203)			
Weekly household income (£)				-5.23x10^{-5}***	-1.95x10^{-5}	1.34x10^{-5}			
				(1.52x10^{-5})	(1.42x10^{-5})	(1.33x10^{-5})			
Constant	0.699***	0.812***	0.606***	0.784***	0.865***	0.637***			
	(0.00133)	(0.00154)	(0.00316)	(0.0107)	(0.01000)	(0.00997)			
R-squared							0.001	0.017	0.021
Observations	282,997	282,997	282,997	194,214	194,214	194,214	184,673	184,673	184,673
Number of accounts	159,100	159,100	159,100	108,050	108,050	108,050	60,776	60,776	60,776
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. Table 3.7 replicates Table 3.6 specifications but months with multiple consumption categories or merchant codes are added to the sample (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.5 Conclusions

Research on mental accounting has extensively probed violations of the commonly assumed fungibility of money and has convincingly argued that the labeling of mental budgets, the allocation of money and the sources of income can have an important influence on consumers' choices (Prelec and Loewenstein, 1998; Thaler, 1999). Much of the early evidence, however, came from studies using judgments of hypothetical spending and repayment scenarios and from non-representative samples of young adults.

Subsequent empirical investigations of mental accounting have shifted toward observational field studies (Beatty et al., 2014; Kooreman, 2000; Milkman and Beshears, 2009), as well as one experimental field study (Abeler and Marklein, 2017). However, most of these studies have focused almost exclusively on the issue of labeling—that is, of whether earmarking payments for particular purposes affects the way they are spent, even when individuals would naturally spend more on the category of consumption than the amount of the earmarked payments.

In this paper, we use credit card data to test a specific prediction of a theory of mental accounting proposed by Prelec and Loewenstein (1998): whether debt incurred on consumables is more likely to be paid off more rapidly than debt incurred on durables. Analyzing data on credit card usage and repayment behaviour provided by five UK credit card issuers, we provide strong support for this prediction of the theory. In a series of analyses that based on different subsets of the data including both new and older credit card accounts, and that incorporate different configurations of controls including random effects and individual fixed effects, we find that this effect of purchase type on the propensity to repay is strong and robust. Repayment of non-durable goods is an absolute 10% more likely than repayment of durable goods. The size strength of this relationship is comparable to an increment in 15 percentage points in the credit cards' APR—an economically large relationship. We hope these results will motivate a deeper investigation of the mental accounting implications on consumer choice.

Although our evidence provides support for the prediction it was intended to test, inevitably, there limitations to our analysis. One is that there was some arbitrariness in the division of spending categories used to catalogue the nature of consumption. We carefully chose our original classification based on the previous literature, and this was the first and only classification we have tested.

After the initial analysis we conducted, and report here, we ran tests designed to assess the robustness of the estimated effects under alternative classification schemes. Unfortunately, however, we do not have data on the exact product or service purchased in an individual transaction. Furthermore, we were unable to filter the impact of other important determinants of repayment behaviour, such as the sources of income or the locations of funds cardholders use for repayment, due to data constraints. These may be other dimensions of the credit card spending and repayment decisions in which mental accounting might be relevant. Our analysis, however, attempts to reduce these concerns by controlling for differences in socioeconomic status, using proxies of income deprivation in the area surrounding the cardholder postcode, and by controlling for unobserved (time constant) heterogeneity among cardholders.

These results have diverse implications for managerial decision making. First, focusing specifically on credit cards, they point to potential new innovations that could give credit cards a strategic advantage. Repayment options currently are focusing on the amount to be repaid, with typical options being the minimum amount to avoid a penalty charge, the last statement balance, or the full current balance. The results just presented suggest, however, that credit card issuers could potentially attract customers by offering repayment options that permit repayment of specific purchases as opposed to amounts. This would increase the tightness of ‘coupling’ of purchases and payments, which, according to Prelec and Loewenstein’s (1998) model, should increase the pain of paying for goods and services, but decrease the pain of paying off the credit card. Similar strategies could be employed for other financial instruments via, for example, the partitioning of spending and savings accounts (see Loewenstein et al., 2012). Second, and more generally, the notion of pain of paying, reinforced by these new findings, could have diverse implications for the delivery of incentives. In many situations, managers are interested in increasing the impact of incentives, e.g., for employees or customers, and in these situations the value of incentives could be enhanced by delivering them in the form of earmarked payments aimed at expenses that individuals find it painful to pay for. For example, although from an economic perspective, customers should be indifferent to whether a discount is applied to an overall purchase, or to some specific component of that purchase (e.g., the cost of the good itself, taxes, or shipping), customers may find some of these components more painful to pay for than others; and firms could benefit from framing a discount as being applied to those components. Likewise, special bonus rewards provided to employees for engaging in specific behaviours, such as engaging with a wellness program or achieving high rates of customer satisfaction, could again be targeted to paying off expenses that employees dislike paying for—e.g., dental insurance premiums, parking, or other commuting costs. As these examples suggest, managers have barely begun to take advantage of the diverse opportunities available for exploiting variability in the pain of paying, both across situations and people (see Rick et al., 2008).

In sum, our analysis provides a new theoretically grounded data point in a growing body of empirical research documenting systematic violations of the predictions of standard consumer theory in ways predicted by theories of mental accounting.

Chapter 4

You Only Watch When You're Winning: Selective Attention Among Individual Investors

4.1 Introduction

When making financial decisions, individuals face financial choices but also face the additional choice of how much attention to pay to their financial situation. Traditional economic theory assumes that individuals allocate resources—including their attention—rationally, choosing to be optimally attentive in light of competing needs and limited time resource (Sims, 2003). However, recent empirical studies show that individuals allocate their attention in non-rational ways, including not paying attention to sales taxes (Taubinsky and Rees-Jones, 2017) or avoiding paying attention to negative checking account balances (Pagel, 2018). Understanding how individuals allocate attention in practice is important for understanding individual financial behaviour and developing realistic models of financial market interaction.

In this chapter, we study how individual investors allocate attention to their trading accounts. Existing studies have found that investors allocate much more attention to their accounts than is explained by the functional need to make trades. For example, Sicherman et al. (2015) find that investors log in to view their account position on average 40 times more frequently than making a trade. Recent studies find that investor attention measured through logins, differs depending on whether the investor's portfolio is making gains or losses (Gherzi et al., 2014; Sicherman et al., 2015). This raises the question of what drives investors to devote attention to their investment accounts, if it is not primarily the need to trade.

We draw upon detailed data from Barclays Stockbroking, one of the UK's largest execution-only trading platforms for individual investors. The data covers a large sample of investors over a multi-year panel, with detailed information on investor characteristics and records of daily login behaviour. A key advantage of our data is that we can observe the exact portfolio holdings of investor on a daily basis. This allows us to match in data on security prices and performance.

This rich data allows us to go beyond previous studies, which have explored the relationship between movements in aggregate index prices and individual login behaviour. Studies adopt this approach of relating aggregate index movements to individual attention despite much evidence in the previous literature that most investors holding only a few stocks (Barberis and Huang, 2001; Barberis, 2018; Goetzmann and Kumar, 2008). Unlike those studies, in ours we can examine how investors respond to movements in the prices of the stocks in their own portfolios, and also examine the dynamics of attention around the time of investors' trading activity.

Our main contribution is to show that investors allocate attention to their portfolios in ways consistent with attention being allocated to optimize hedonic utility (i.e., the satisfaction or pain arising from observing movements in the value of a portfolio).

We build this contribution upon three findings. First, we find that investors log in much more frequently than they trade, suggesting that logging in derives a significant hedonic utility component for the individual investor. In our sample of individual investors, the ratio of logins to trades is approximately ten-to-one. Hence, most logins are unconnected to trading activity. This ten-to-one ratio is not as high as in the sample of 401k accounts used in Sicherman et al. (2015). However, 401k long-term saving accounts differ in many aspects compared with the brokerage accounts in our data. Hence, we might expect that 401k accounts are particularly inactive in trades as individuals set contribution limits via their employer and are unlikely to trade within the 401k plan. In our sample, both occasional and regular traders log in much more frequently than they trade.

Second, we find evidence for Ostrich effects in investor attention. Previous studies have concentrated on the relationship between aggregate market index movements and investor login behaviour. Instead, we examine the relationship between price movements of the stocks within the investor's portfolio and login behaviour. Focusing on reactions to price movements after buy-trades, we show that investors who make price gains on recent buy trades log in more than investors who make price losses (or who see prices unchanged). These effects are seen among investors with both thick and thin portfolios, and persist over multiple weeks following the buy-trade. These patterns are consistent with models of hedonic utility in which individuals are averse to experiencing losses on their portfolios.

Third, we show that the allocation of attention to portfolios varies with the opportunity cost of time. Using shocks of local weather, we show that on sunny days investors are less likely to view their portfolios. This suggests that the utility value of good-weather leisure is a substitute for the hedonic utility value of viewing the portfolio position. We implement this analysis using matched postcode data on local weather, conditioning on both region and day fixed effects.

Our findings also relate to the broader study of attention. Gabaix (2017) distinguishes between optimal inattention under which attention is allocated to maximize individual utility and behavioural attention, whereby attention is allocated by behavioural biases. Gabaix (2017) suggests different measures of attention including inferring inattention from sub-optimal behaviour (i.e. assumed inattention), survey measures of time spent paying attention and proxy measures of attention, such as logins. Our use of logins as a proxy measure of attention is facilitated by the rise of online-only trading platforms and is a reliable measure by virtue of the automated, machine driven collection of the login records.

Our results have implications for models of attention. While the canonical model of optimal inattention of Sims (2003) assumes that individuals allocate attention rationally, our results show a strong hedonic utility role for the allocation of attention. Investors appear to be loss averse to experienced losses. Much evidence exists for loss aversion (Kahneman and Tversky, 1982). Loss aversion has been suggested as an explanation for the equity premium puzzle, and the under-diversification positions of many investors (Barberis and Huang, 2001; Barberis et al., 2016). However, our results are consistent with a model of aversion to observed losses, even when those losses are not realized. Hence, investors may be averse to seeing losses on their accounts, as well as being averse to realising those losses in their trading activity.

Prior studies have also suggested that individuals allocate attention in sub-optimal ways. DellaVigna (2009) shows that investors are under-responsive to earnings announcements that are released on Friday afternoons, distorting trading behaviour. Taubinsky and Rees-Jones (2017) show that investors are unresponsive to changes in sales taxes which are not salient in posted prices in retail stores.

Our study also contributes to the broader literature on the behaviour of individual investors. The prior literature shows that although the optimal portfolio diversification strategy is long-established (Markowitz, 1952), most investors hold only a few stocks in their portfolio (Barber and Odean, 2013; Goetzmann and Kumar, 2008). Investors also exhibit biases in their trading behaviour, such as over-trading and rank effects (Barber and Odean, 2000, 2001; Hartzmark, 2014). Our findings contribute to the study of the role of psychology in investor behaviour (Barberis, 2018) and more broadly to the application of psychology to economic decision making (DellaVigna, 2009).

4.2 Data

We use anonymous individual investor account level panel data provided by Barclays Stockbroking, a large UK based execution-only brokerage platform. Barclays Stockbroking offers a competitively priced platform, offering the ability to trade individual stocks, mutual funds and a range of retail focused securities. Data were provided by Barclays for the purpose of academic research, with no constraint on the research agenda.[1] The data set provided by Barclays contains a total of 155,309 accounts, including accounts which opened and closed, during the period April 02, 2012 to March 29, 2016. During this period, there were no significant changes to the Barclays Stockbroking platform.[2]

4.2.1 Trading Account Types

The majority of investors hold non-tax favored trading accounts with no limits on investment sizes or withdrawals. Hence, attention and login activity is unlikely to be affected by rules regarding withdrawal limits or the allowable timing of withdrawals. The Barclays Stockbroking platform offered a range of account types, all of which were execution-only, but differed in taxable status and liquidity. The majority of accounts are tax liable direct investing accounts,

[1]Barclays Stockbroking have not reviewed this manuscript.

[2]Subsequently, Barclays have substantially overhauled their execution-only brokerage platform which has also been re-branded to Barclays SmartInvestor.

with no limits on investment amounts or withdrawals. Additionally, 24% of accounts are Retail Individual Savings Accounts (ISA). ISA investments are non-tax accruing, with caps on maximum annual investment amounts, which are likely to limit login activity once the maximum buy amount limit is reached. A further 3% of accounts were money-purchase Self-Invested Personal Pensions (SIPP), which are also non-tax accruing and have no option to withdraw funds until a set retirement age. Fewer than 1% of accounts correspond to other categories (such as Advisory Dealing Accounts, Corporate ISA, Advisory ISA).

4.2.2 Description of Key Variables

Most accounts in the dataset trade individual stocks listed on the London Stock Exchange (LSE). Trading of more complex securities is uncommon among European retail investors. During the data period, trading in diversified products such as Mutual Funds and Exchange Traded Funds (ETF) had not yet reached popularity in the UK, with only 18% of accounts trading Mutual Funds or ETFs at least once during the period. As we show later, investors trading these diversified products differ in their login frequency compared to investors trading individual stocks.

The dataset contains information on investor characteristics, account logins (by day) and very detailed data on account activity and positions. Investor characteristics (measured once in the dataset at account opening) include investor age, gender and account tenure. The dataset contains dated observations of every login to the account. All account activity is recorded in the data, including buy and sell trades, stock-splits and account management fees and charges. The account activity data includes details on individual positions bought and sold, including stock identifiers. We use these identifiers to match in data on individual stocks and securities from Datastream.

In addition, the data set contains quarterly records of portfolio balances on all positions in the portfolio. Combining these quarterly stock position data with the daily buy and sell flow data, we are able to recreate individual account portfolios at daily frequency. Also, in cases where investors transfer accounts into Barclays Stockbroking from another investment platform, we observe the details of all positions transferred in and hence we can also recreate portfolios for these account types.

The ability of observing portfolio details at the daily level is particularly advantageous for studying investor attention. Many studies document that individual investors tend to hold only a few stocks (Barber and Odean, 2013; Goetzmann and Kumar, 2008). Hence, we might expect that investors are particularly attentive to the price movements of the small number of stocks they hold, rather than to aggregate indices (e.g., the FTSE100) which will have little information about price movements for the stocks they actually hold. Whereas Sicherman et al. (2015) examine the relationship between aggregate index movements and individual login behaviour, we are able to examine the relationship between movements in prices of the specific stocks held by investors and investor login behaviour.

4.2.3 Sample Selection

Our interest lies in investor attention, measured by login activity. We therefore make the following sample selections to create a *baseline* sample. We start our analysis with a representative 10% random sample of accounts, including 15,013 accounts in total. The unit of observation in the data is an account $\times$ day. First, we drop observations for dormant accounts. We drop account $\times$ days during periods of at least one year in which the account made no login or trade, as these long periods of inactivity suggest that the account is dormant. The remaining observations allow us to define cycles of account activity. Additionally, we drop all cycles that have fewer than two logins and two transactions, as in these cases we cannot observe the period between transactions and, fundamentally, the period between logins, which is our main measure of attention. Second, we drop all observations for accounts for which we cannot reconstruct portfolios due to missing prices data (this arises when accounts have positions in securities for which no label is provided), and also for accounts for which there is missing demographic data (the age and gender variables are missing). Finally, we also drop the top and the bottom 1% of accounts by average portfolio value over the sample period to avoid results being driven by a very small sample of very high wealth individual investors, or the other way around. The lower bound threshold for removing the top 1% of accounts by average value is £2,100,377, while the bottom 1% is £44.30.

Table 4.1 shows the results of these steps in sample selection. Of the 6,623 accounts dropped due to sample selection, 59.9% are dropped due to account inactivity. The baseline sample retains 55.9% of accounts. The other steps in sample selection drop only 23.1% of days with logins and only 27.7% of days with transaction. The baseline sample is unbalanced, i.e., accounts open and

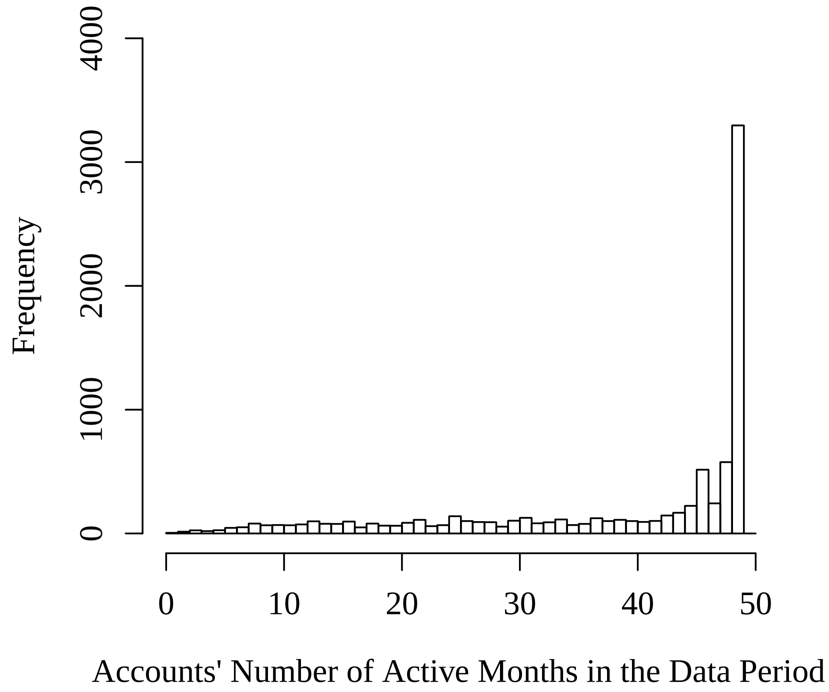


Fig. 4.1 Distribution of accounts by number of months in the baseline sample. Histogram of the number of months accounts are active in the data. Active account defined as as an account with at least two login-days and at least two transaction-days during a period of activity. A period of activity compromises any year or consecutive years in which the account has at least one login-day per year.

close during the sample period. Figure 4.1 shows the distribution of accounts by number of months for which they are present in the baseline sample. The majority of accounts are in the sample for the entire period, with only a small minority of accounts present for less than half of the full sample period.

4.2.4 Baseline Sample Summary Statistics

Table 4.2 provides summary data for the baseline sample. Panel A summarizes investor demographic characteristics. The majority of account holders are male. The average age of an account holder is 54 years. Account holders have held their accounts for, on average, 5 years.

Panel B summarizes account characteristics. The average portfolio value (calculated by first taking the average portfolio value of an account, and then averaging across all accounts) is close to £55,000. However, the distribution of account portfolio values has a long right-tail. The average value is higher than the 75th percentile, and the median portfolio value is £15,000.[3].

In keeping with the evidence of prior studies, our sample of UK investors hold portfolios that are highly concentrated in only a few stocks. Accounts have less than 7% of their portfolio invested in mutual funds. The number of stocks held is on average only 5, and at the median only 3.

The final two rows of Table 4.2 summarize login and transaction activity at the monthly level. On average, accounts show at least one login in 73.1% of months in which they are present in the data, at the 75th percentile accounts show logins in every month in which they are present in the data. Accounts on average show logins more frequently than they show trades. On average, accounts show at least one transaction in 27.6% of months in which they are present in the data.

[3]Note that these summary data are for the baseline sample having dropped the top 1% of accounts by portfolio value. The top 1% contains some accounts with portfolio values in the hundreds of millions of UK pounds.

Table 4.1 Data Cleaning

	Number of Accounts	Number of Login-Days	Number of Transaction-Days
Starting Sample	15013	3000249	264409
Drop due to:			
Inactive Accounts	3967	238458	2099
Unmatched Prices	1454	299006	34914
Demographic data absent	1028	355651	34620
Top and Bottom 1% by Portfolio Value	174	39044	3735
Baseline sample	8390	2068090	189041

Note. The starting sample is a 10% random sample of the total number of accounts.

Table 4.2 Baseline Sample Statistics

	Mean	SD	Min	Max	p25	p50	p75
A. Card Holder Characteristics							
Female = 1	0.22						
Age (years)	53.89	14.08	27.00	77.00	47.00	57.00	67.00
Account Tenure (years)	4.98	3.40	0.07	16.95	2.78	3.99	6.49
B. Account Characteristics							
Portfolio Value (£1000)	54.73	148.77	0.04	2100.38	4.50	15.21	44.28
Investment in Mutual Funds (£1000)	4.29	31.16	0.00	1497.42	0.00	0.00	0.00
Investment in Mutual Funds (%)	6.86	20.32	0.00	100.00	0.00	0.00	0.00
Number of Stocks	4.92	5.51	0.02	69.04	1.48	3.11	6.26
Months w/ logins (%)	73.13	26.29	8.33	100.00	51.22	81.25	100.00
Months w/ transactions (%)	27.57	21.54	2.08	100.00	11.11	20.83	37.50
N	8390						

Note. Statistics for the baseline sample of accounts defined in Table 4.1. Portfolio value, investment in mutual funds and number of stocks are account average measures. Account tenure is defined since the account open date (available for 62% of the accounts). When the open date was unavailable, is was defined since the first record of login in the data period April 2012 to March 2016.

4.3 Frequency of Logins vs. Frequency of Trades

We begin our analysis of investor attention to their accounts by comparing login activity with transaction activity. In keeping with Sicherman et al. (2015), we find that investors log in much more frequently than they trade. We then explore the determinants of investor login activity.

For each account, we calculate the frequency of login-days and the frequency of transaction-days (days on which a buy or sell transaction is made).[4] Because our account data contain account openings and closings, the panel is unbalanced. We calculate the frequency of logins as the account-level average distance (in days) between login-days and the frequency of transactions as the account-level average distance (in days) between transaction-days.

Figure 4.2 illustrates the distributions of login frequency, trading frequency and the correlation between the two.[5]

Panel A of Figure 4.2 illustrates the correlation between frequency of logins (shown on the y-axis on a scale of 0–40 days) and frequency of trades (shown on the x-axis on a scale of 0–400 days). The plot shows a clear positive relationship between login frequency and trading frequency, but that logins are much more frequent than trades across the full distribution of login and trading frequency. The line of best fit has a slope of approximately 0.1, implying that accounts log in approximately ten times more frequency than they trade. Notably, a linear line of best fit fits the data reasonably well, with the data showing a little concavity in the top-right quadrant. Hence, login frequency is much higher than trading frequency for accounts that are very active in logging in and trading (located in the bottom-left quadrant of the plot) and for accounts that are less active (located in the top-right quadrant of the plot).

Panels B and C illustrate the distributions of login frequency and trading frequency. These two marginal distributions have similar shapes. Approximately 4.91% of accounts log in every day, with 45.12% of accounts logging in on average at least once per week. Panel B illustrates the frequency of trades. Notably, the density of high-frequency trade accounts is far lower than that

[4]Our definition of transaction-days excludes automatic transactions, such as automatic dividend reinvestments. Hence we define a transaction-day as a day on which the investor logged-in to their trading account and made a manual instruction.

[5]In the plots in Figure 4.2, we restrict the data to the bottom 95% of accounts, excluding those who log in in intervals greater than 70 days. Table 4.3 reports summary statistics for these variables from the unrestricted baseline sample.

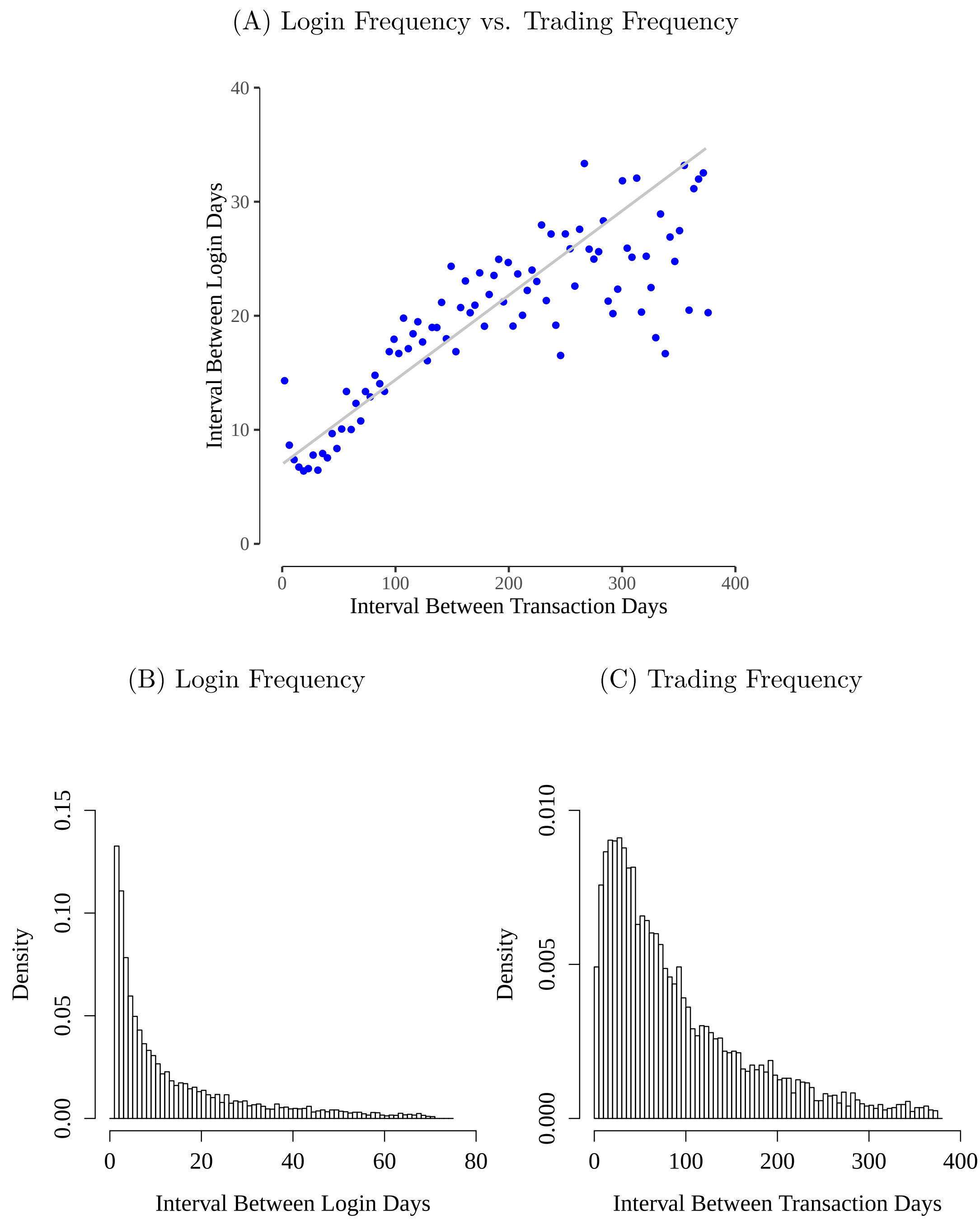


Fig. 4.2 Frequency of logins vs. frequency of trades. Panels A and B show histograms of the account level average distance between days with a login and the account level average distance between days with a trade. Panel C shows a binned scatter plot of the two variables (100 bins). In Panels A and B the baseline sample is further restricted to the bottom **95%** of accounts by the x-axis variable.

Table 4.3 Logins Summary Statistics

	Mean	SD	Min	Max	p25	p50	p75
Interval Between Logins (days)	18.80	27.69	1.05	377.67	3.22	8.48	22.85
Interval Between Transactions (days)	114.66	135.86	1.00	1379.00	32.60	70.50	144.29
Ratio of Login Days to Transactions Days	20.43	35.48	1.00	602.50	5.00	9.69	21.10
N	8390						

Note. The intervals between login-days and the intervals between transaction-days are account average measures.

of high frequency login accounts. Only 3.58% of accounts trade on average at least once per week.

Table 4.3 provides summary data on the frequency of logins and trades. Accounts see logins on average every 19 days, but see transactions every 115 days. At the median, accounts see logins every 8 days but trades only every 71 days. The bottom row of Table 4.3 shows the ratio of login-days to transactions days. This is calculated as the total number of login-days for an account during the period in which the account is present in the baseline sample, divided by the total number of transaction-days for an account during the period in which the account is present in the baseline sample. At the median, the ratio takes a value close to 10, implying that accounts log in 10 times more frequently than they trade. The mean value is nearly double this, driven by a small number of accounts that log in very frequently (including the small subset of accounts that see logins every day of the sample period).

The tendency of investors to log in much more frequently than they trade suggests that in our data sample, as in Sicherman et al. (2015), login activity has a strong hedonic component. Most login activity is evidently not for the purpose of making transactions alone. Hence, investors are clearly logging in most of the time in order to purely view their accounts. Even if investors log in once to place a transaction order and then again to check that the order has been executed (most likely logging in the next day), such behaviour cannot account for investors logging in ten times more frequently than they trade.

4.3.1 Correlates of Login behaviour

In this section, we explore the correlates of login behaviour. To do so, we estimate parsimonious Ordinary Least Squares (OLS) regression models. In our baseline cross-sectional model specification, the dependent variable is the account-level average interval between logins, measured in days. Hence, each account contributes one observation to this cross-sectional model.

Table 4.4 reports results from the cross-sectional OLS regression model. The specification in Column 1 includes only investor characteristics—age and gender. The specification in Column 2 adds controls for the portfolio value (the account-level average value of the portfolio over the sample period) and the number of transaction days per month. Column 3 adds the number of stocks held in the portfolio (the account-level average over the sample period) and a dummy indicating whether the portfolio includes an investment in mutual funds during the data period. All models include a constant term and geographic region of residence fixed effects.

Results in Column 1 show that women have a longer average interval between logins compared to men. The coefficient value of 3.6 on the female dummy in Column 1 implies that female investors have an average interval between logins that is 3.6 days longer than the male average. With the addition of controls in Columns 2 and 3, the coefficient falls to 2.0, but remains precisely defined. The sample average overall is 18.8, and so two additional days are comparable to 10% of the number of days between logins for the average investor.

Results in Column 2 show that the interval between logins decreases with the number of trades per month. This relationship is in part mechanical because investors have to log in to their accounts in order to make a trade. Conditional on this, results in Columns 2 and 3 show that the interval between logins decreases with the size of the investor's portfolio and decreases with the number of stocks. The relationship between number of stocks and intervals between logins is non-monotonic, with the coefficient estimates implying the interval between logins is shorter at the third quartile of the number of stocks compared with the fourth quartile. These coefficient estimates are consistent with investors paying on average more attention to their portfolios as the financial stakes increase (portfolio value) and with the complexity of the portfolio (number of stocks held).

We further explore the correlates of login behaviour using data on within-investor changes in login behaviour over time. There may be important stable individual differences in login behaviour, such as personality, that cannot be controlled for in a cross-section regression. Therefore, we also present panel (fixed-effects) estimates. To conduct this analysis, we take within-quarter averages of time-varying variables (e.g., the time-varying measure of the account portfolio value is the average portfolio value within the quarter). We then estimate models with account fixed effects. The advantage of these models is that they control for account specific time invariant unobserved heterogeneity.

Table 4.4 Interval Between Logins, Pooled OLS Models

	(1)	(2)	(3)
Female=1	3.566***	2.013***	1.958***
	(0.734)	(0.655)	(0.652)
Investor Age			
(*ref: 27 year old or less*)			
28 - 37 years old	1.628	1.166	1.035
	(1.446)	(1.287)	(1.280)
38 - 47 years old	2.594	3.210**	2.778*
	(1.408)	(1.264)	(1.258)
48 - 57 years old	-1.347	1.265	0.910
	(1.378)	(1.253)	(1.247)
58 - 67 years old	-2.817	0.966	0.698
	(1.453)	(1.331)	(1.325)
68 or more years old	-2.819	1.489	1.219
	(1.518)	(1.394)	(1.391)
Portfolio Value			
Quartile 2		-2.327***	-1.126
		(0.775)	(0.787)
Quartile 3		-4.703***	-2.666***
		(0.793)	(0.845)
Quartile 4		-6.635***	-4.313***
		(0.837)	(0.932)
Number of Stocks			
Quartile 2			-2.278***
			(0.771)
Quartile 3			-4.267***
			(0.821)
Quartile 4			-2.093*
			(0.940)
Number of Trade Days per Month'			
Quartile 2		-15.198***	-15.104***
		(0.760)	(0.758)
Quartile 3		-26.094***	-25.767***
		(0.766)	(0.773)
Quartile 4		-31.574***	-31.423***
		(0.781)	(0.801)
Investment in Mutual Funds = 1			-5.638***
			(0.718)
Constant	16.545***	38.653***	40.507***
	(4.411)	(3.962)	(3.955)
Observations	8390	8390	8390
Adjusted R-squared	0.0077	0.2185	0.2274
Region FE	Yes	Yes	Yes

Note. Regressors included in the estimation correspond to average measures by account. Portfolio value and number of stocks were measured on the first business day of the month and then averaged across months. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38; and for the number of stocks, Q1: 0.02 to 1.48, Q2: 1.48 to 3.11, Q3: 3.11 to 6.26, and Q4: 6.26 to 69.04 stocks. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

Table 4.5 Interval Between Logins, Individual Fixed Effects Models

	(1)	(2)
Log Portfolio Value (£1000)	-2.468***	-3.322***
	(0.161)	(0.179)
Number of Stocks		0.422***
		(0.046)
Number of Trade Days per Month	-4.567***	-4.620***
	(0.134)	(0.134)
Investment in Mutual Funds = 1		2.979***
		(0.750)
Observations	91402	91402
Number of Accounts	8214	8214
Adjusted R-squared	0.3554	0.3563
Account FE	Yes	Yes

Note. Regressors included in the panel data estimation are quarter average measures by account. Investment in mutual funds is a dummy equal to one when the investor's portfolio had any mutual fund during the quarter. A fewer number of accounts than the baseline total is included in the regression. This reduction is because the panel regression requires at least two quarters of activity. So the accounts that have a short active period of less than two quarters (or less than three logins-days in two different quarters) are omitted. Standard errors in parentheses. Significance levels: *** p<0.01,** p<0.02, * p<0.05.

Results are shown in Table 4.5. Results in Column 1 show that accounts containing higher valued portfolios log in more frequently, confirming the cross-sectional relationship. A £1,000 increase in the log portfolio value is associated with a 2.47 days reduction in distance between login-days. The coefficient on the number of days with trades per month implies that an account with one additional trade per month has an interval between login-days which is 4.6 days shorter.

The model shown in Column 2 include measures of diversification: the number of stocks held in the portfolio and whether the portfolio includes an investment in mutual funds during the quarter. The coefficients on both of these variables are positive, implying that more diversified accounts have a longer period between logins. This is consistent with more diversified investors paying less attention to the performance of individual stocks. The coefficient magnitudes imply that a portfolio with one additional stocks has a 0.4 days longer interval between logins, and that during the quarters in which the investor holds a mutual fund the interval between logins is 3.0 days longer. These coefficients have reversed sign compared to those in Table 4.4. However, these models include account fixed effects and are therefore identified from within-person changes in account positions over time, ruling out the confound that investors who diversify more may be different in their attention behaviour to those who diversify less.

4.4 Selective Attention I: Stock Prices and Login Behaviour

In the final two sections of the chapter, we use two natural experiment to examine how investor attention varies with the hedonic utility value of attention. First, in this section we examine patterns in login behaviour in the period following trades, with a specific interest in differences in login behaviour among investors making gains (which yield positive hedonic utility) and losses (which yield negative hedonic utility) from recent trades. Second, in the next section we examine how login behaviour varies with good weather (which raises the opportunity cost of paying attention to the account). Both of these natural experiments generate variation in the hedonic value of paying attention to the investment account.

Existing studies examine the relationship between investor attention and movements in stock market prices (Gherzi et al., 2014; Sicherman et al., 2015). These studies find either the well-known "Ostrich" effect, whereby attention falls in light of bad news, such as declines in the market index, or the alternative "Meerkat" effect, whereby investors increase their portfolio monitoring following both positive and daily negative market returns. One shortcoming of using the market index is that, as is well documented in the literature on individual investor behaviour, most investors do not hold index funds but instead pick a small number of stocks (Barber and Odean, 2013; Goetzmann and Kumar, 2008). Hence, movements in the value of the index are likely to be relevant only for a small subset of investors.

With our rich data on the portfolio positions of individual investors, we can exploit the investor-specific information on portfolio positions and logins to analyse the relationship between login activity and movements in the prices of the particular stocks held by an investor. Specifically, we study the login behaviour of investors on days following a buy-trade. We examine how investor login behaviour varies by losses and gains on the specific stock purchased via the buy-trade.

From the baseline sample, we restrict to the sub-sample of accounts that make at least one buy-trade in the sample period, remain in the data for at least 5 days after the day of the buy-trade, and have no other trades (buy or sell) in the 5 days period after the first buy-trades.[6] This restriction removes only a modest proportion of accounts, providing 6,456 accounts for analysis. We then examine login behaviour over the 5-day period following the day of the buy-trade.

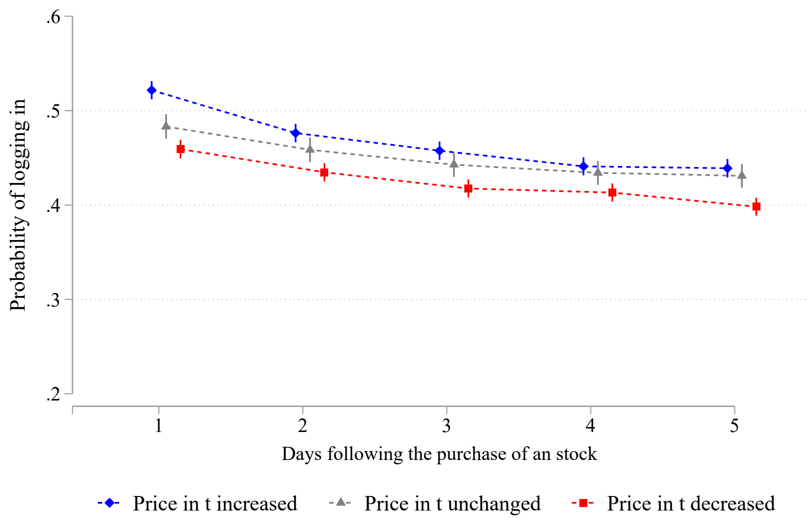
Figure 4.3 illustrates the main results. Panels A and B illustrate the probability of a login on the 5 days following a buy-trade (day 0). The sample is split into three groups by the change in price on the stock purchased via the buy-trade: price increases (the blue line), decreases (the red line) and prices unchanged (to the nearest penny, the grey line). In Panel A, the reference price is the price the day before, in Panel B the reference price is the price on the day of the buy-trade (day 0).[7] By construction, all investors in the sample log in on the day of the buy-trade, day 0, to place the order. Figure 4.4 illustrates the distribution of price changes over the 5 day period following the day of the buy-trade. The distribution of returns is very close to a normal distribution.

The pattern seen in both panels A and B of Figure 4.3 is that, on the days following the buy-trade, investors are more likely to log in if the stock has increased in price, or remained unchanged, compared to if the stock had decreased in price. This is true under both definitions of price change based on the two reference groups. The effect is also seen on each of the five days following the day of the buy-trade.

[6] We make this additional restriction in order to remove any effects of login behaviour arising due to multiple trades. This restriction drops only a small number of accounts that make trades in close succession.

[7] Individual investors may focus on price changes since the day of the buy-trade, as suggested by evidence for the disposition effect.

(A) Return Day t vs. Day t-1



(B) Return Day t vs. Purchase Day 0

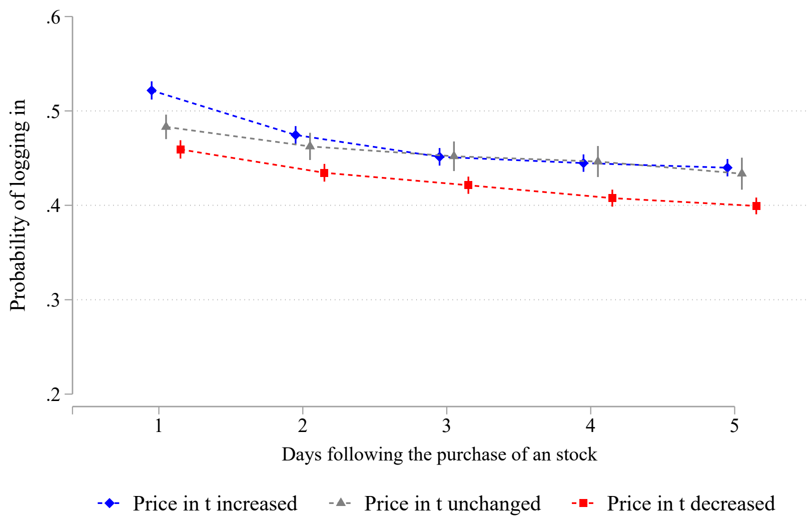
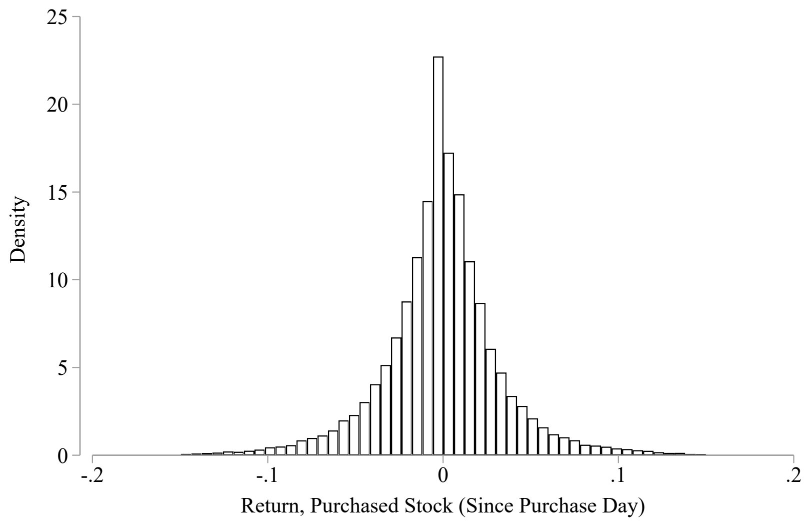


Fig. 4.3 Probability of logging in by price change of most recent purchased stock. The top panel shows the raw likelihood of logging in during the 5 business days following the purchase of an stock, excluding bank holidays, according to changes in the daily return of that stock; while the bottom panel, according to changes in the return of that stock since the purchase day. The probability of logging in is displayed for the cases in which the trader has a portfolio of stocks and buy a new stock or has one or more stocks in his portfolio and increase his position in one of these stocks (26,166 weeks from 6,456 accounts). In all weeks, no other transaction has taken place. Figures C.1.1 and C.1.2 distinguish patterns of logins for each of these cases. Histograms of returns for the week following the transaction are shown in Figure 4.4. Lines span 95% confidence intervals.

(A) Return Since Purchase Day



(B) Daily Return]

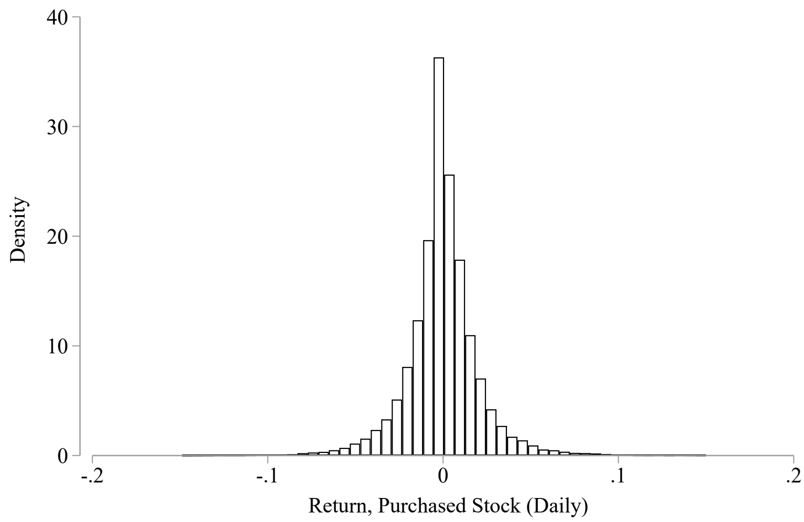


Fig. 4.4 Distribution of stock returns. Panel A displays the daily return since purchase of stocks during the following five business days after the purchase, excluding the weeks in the top/bottom 1% of returns. Panel B displays the daily return (day t vs day $t-1$) of stocks during the following five business days after the purchase, excluding the weeks in the top/bottom 1% of returns. Weeks included are those in which the trader bought only one stock and make no other transaction during the week (21,315 weeks from 6,077 accounts).

In Appendix C, we show that this difference in login behaviour by increase / decrease in price of the stock purchased holds true across accounts by different types of portfolio positions on the buy-day, such as accounts with or without other stocks in the portfolio. Figure C.1.1 shows that the same pattern is seen in response to daily price changes after buy-days in accounts with single stocks, in accounts with multiple stocks when buying a new stock, and in accounts with multiple stocks when topping-up a position in an existing stock. Figure C.1.2 shows that these patterns are the same when using the buy-day as the reference day. The same pattern is also seen when the time-period after the buy-day is extended to 20 business days (a month), illustrated here in Figure 4.5 for all buy-days and in Appendix C, in Figures C.1.3 and C.1.4, for the same three subsets of buy-days as shown in Figure C.1.1, but extended to the 20-day period.

We use an econometric model to estimate the strength of the relationship between movements in prices of the stock purchased on the buy-day and login behaviour. Table 4.6 shows results from a baseline model specification in which the dependent variable is a dummy variable indicating whether the account logged in at least once during the day. Logins are studied from the first week after the buy-day (Column 1) to the fourth week after the buy-day (Column 4). Each week is composed by 5 business days. Observing login behaviour over the 4-week period allows us to test whether the price effect on login behaviour is temporary with the purchase of a new stock, or whether the effect persists over time.

Results in Columns 1–4 show that the change in stock prices of the purchased stock have a positive and statistically significant effect on the likelihood of logging in that persist over the 4-week period. The coefficient of the change in price of the purchased stock is constant across the time periods, implying that in each week a 1% increase in the price of the purchased stock raises the probability of logging in by approximately 0.5%.

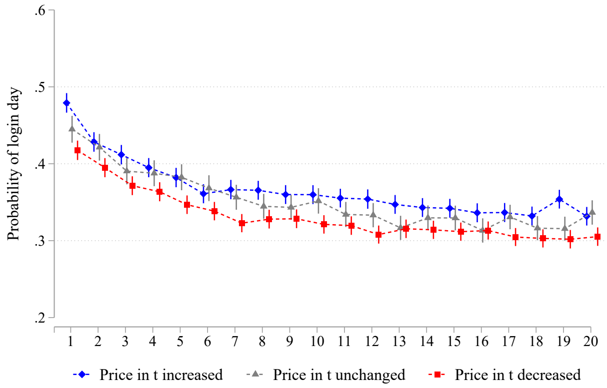
The econometric model also includes as a control the change in prices of other stocks in the portfolio. Again, the coefficient is positive and statistically significant, implying that investors login behaviour is also responsive to changes in the prices of stocks already held by the investor. These estimates are robust to the inclusion of investor characteristics, trading frequency, portfolio value and the number of stocks held in the portfolio.

Table 4.7 presents results from a very similar econometric model to that used in Table 4.6, the only difference being that the change in price is defined from the purchase day, not the previous day. Results are very similar, with positive coefficients on the change in price of the purchased stock and positive coefficients on the change in price of remaining stocks. These positive coefficients are seen in all four weeks after the buy-day.

These results are consistent with investors holding an aversion to observing losses on their accounts. Whereas the disposition effect arguably arises because investors are averse to realising losses, the relationship between login behaviour and losses we see here can be explained by a form of loss aversion in which investors are also averse to experiencing losses (i.e. seeing losses displayed on their portfolio screen). Also, our results, which are consistent with investors not logging in to their accounts when they observe declines in aggregate indices (as in Sicherman et al., 2015), show that investor attention is responsive to losses on the specific stocks held in the investor's portfolio.

In addition, in Tables 4.8 and 4.9 we distinguish the effect of increments in prices from that of reductions in prices. That is, we allow for the effects of changes in prices to be monotonically non-linear (e.g., for the possibility of a kink at zero). The variable '% Change Purchased Stock +' records the changes in prices from 0 (i.e., negative changes take the value of 0); while the variable '% Change Purchased Stock -' records the changes in prices up to 0 (excluding 0) (i.e., positive changes take the value of 0). In most columns, the size of the coefficients for the reductions in prices is higher in magnitude to that for the increments in prices. In Appendix C, in Tables C.1.1 and C.1.2, we observe that this pattern holds even for the second most recent stock purchased, along with the rest of the portfolio. Overall, these findings suggest that the perceived hedonic pain of observing losses is at least twice as great as the impact of observing gains. The fact that losses appear to be hedonically more impactful than gains is again consistent with the notion of loss aversion from Prospect Theory (Kahneman and Tversky, 1979).

(A) Return Day t vs. Day t-1



(B) Return Day t vs. Purchase Day 0

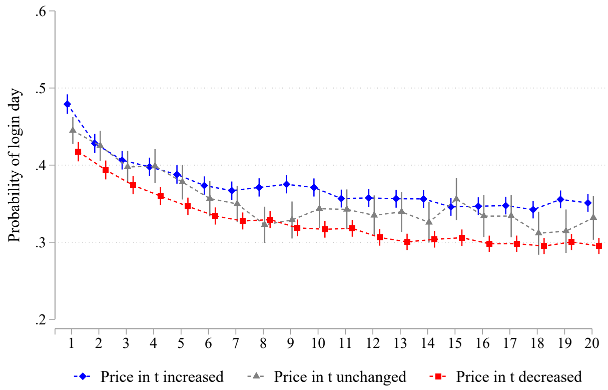


Fig. 4.5 Probability of logging in by price change of most recent purchased stock - Daily price changes, one month window. The top panel shows the raw likelihood of logging in during the 20 business days following the purchase of an stock, excluding bank holidays, according to changes in the daily return of that stock; while the bottom panel, according to changes in the return of that stock since the purchase day. The probability of logging in is displayed for the cases in which the trader has a portfolio of stocks and buy a new stock or has one or more stocks in his portfolio and increase his position in one of these stocks (14,968 months from 5,737 accounts). In all months, no other transaction has taken place. Figures C.1.3 and C.1.4 distinguishes patterns of logins for each of these cases. Lines span 95% confidence intervals.

Table 4.6 Logins and Daily Returns, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock (Daily)	0.005***	0.005***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
% Change, Remaining Stocks (Daily)	0.010***	0.011***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Female=1	-0.006	-0.007	0.002	0.001
	(0.014)	(0.013)	(0.013)	(0.013)
Investor Age				
28 - 37 years old	-0.040	-0.035	-0.047	-0.046
	(0.030)	(0.029)	(0.030)	(0.029)
38 - 47 years old	-0.016	-0.005	-0.007	-0.002
	(0.029)	(0.029)	(0.030)	(0.029)
48 - 57 years old	-0.009	0.003	0.001	0.014
	(0.029)	(0.028)	(0.029)	(0.028)
58 - 67 years old	0.011	0.026	0.023	0.033
	(0.030)	(0.029)	(0.031)	(0.030)
68 or more years old	0.047	0.064*	0.069*	0.078**
	(0.031)	(0.031)	(0.032)	(0.031)
Number of Trade Days per Month				
Quartile 2	0.074***	0.089***	0.080***	0.073***
	(0.016)	(0.015)	(0.015)	(0.014)
Quartile 3	0.169***	0.173***	0.167***	0.166***
	(0.015)	(0.015)	(0.014)	(0.014)
Quartile 4	0.306***	0.314***	0.299***	0.298***
	(0.016)	(0.015)	(0.015)	(0.016)
Portfolio Value				
Quartile 2	-0.022	-0.010	-0.001	-0.000
	(0.018)	(0.018)	(0.018)	(0.018)
Quartile 3	-0.001	0.007	0.022	0.020
	(0.019)	(0.018)	(0.018)	(0.018)
Quartile 4	0.006	0.021	0.032	0.030
	(0.020)	(0.019)	(0.020)	(0.020)
Number of Stocks				
Quartile 2	-0.016	-0.015	-0.027	-0.017
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 3	0.028	0.036	0.027	0.041*
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 4	0.013	0.028	0.015	0.033
	(0.023)	(0.023)	(0.023)	(0.023)
Constant	0.327***	0.263***	0.236***	0.231***
	(0.080)	(0.084)	(0.069)	(0.071)
Observations	58280	58280	58284	58285
Number of Accounts	4669	4669	4670	4670
Adjusted R-squared	0.0607	0.0694	0.0685	0.0727
Region FE	Yes	Yes	Yes	Yes

Note. Columns 1 to 4 display the probability of logging in during the first to fourth weeks following the purchase of an stock (excluding non-business days and bank holidays). The dependent variable is a dummy equal to 1 when there is a login during the day. Only months in which no other transaction occurred after the purchase of the stock are included. The data is also restricted to months in which the cardholders has a portfolio of at least two stocks after the purchase. Change in value of the purchased stock and remaining stocks are computed daily with respect of the value in the previous business day. The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38; and for the number of stocks, Q1: 0.02 to 1.48, Q2: 1.48 to 3.11, Q3: 3.11 to 6.26, and Q4: 6.26 to 69.04 stocks. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

Table 4.7 Logins and Returns Since Purchase, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock (Since Purchase)	0.003***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
% Change, Remaining Stocks (Since Purchase)	0.007***	0.006***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Female=1	-0.006	-0.007	0.003	0.001
	(0.014)	(0.013)	(0.013)	(0.013)
Investor Age				
28 - 37 years old	-0.040	-0.035	-0.048	-0.048
	(0.030)	(0.029)	(0.030)	(0.029)
38 - 47 years old	-0.017	-0.005	-0.008	-0.005
	(0.029)	(0.029)	(0.030)	(0.029)
48 - 57 years old	-0.009	0.003	-0.000	0.011
	(0.029)	(0.028)	(0.029)	(0.028)
58 - 67 years old	0.011	0.026	0.021	0.030
	(0.030)	(0.030)	(0.031)	(0.030)
68 or more years old	0.048	0.064*	0.068*	0.076**
	(0.031)	(0.031)	(0.032)	(0.031)
Number of Trade Days per Month				
Quartile 2	0.075***	0.089***	0.079***	0.071***
	(0.016)	(0.015)	(0.015)	(0.014)
Quartile 3	0.169***	0.174***	0.167***	0.165***
	(0.015)	(0.015)	(0.014)	(0.014)
Quartile 4	0.307***	0.316***	0.301***	0.299***
	(0.016)	(0.015)	(0.015)	(0.016)
Portfolio Value				
Quartile 2	-0.022	-0.013	-0.004	-0.003
	(0.018)	(0.018)	(0.018)	(0.018)
Quartile 3	-0.001	0.005	0.019	0.017
	(0.019)	(0.018)	(0.018)	(0.018)
Quartile 4	0.005	0.017	0.027	0.024
	(0.020)	(0.019)	(0.019)	(0.019)
Number of Stocks				
Quartile 2	-0.017	-0.016	-0.029	-0.018
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 3	0.028	0.034	0.024	0.039
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 4	0.013	0.025	0.012	0.029
	(0.023)	(0.023)	(0.023)	(0.023)
Constant	0.328***	0.272***	0.247***	0.246***
	(0.080)	(0.085)	(0.070)	(0.071)
Observations	58280	58280	58280	58280
Number of Accounts	4669	4669	4669	4669
Adjusted R-squared	0.0611	0.0708	0.0705	0.0756
Region FE	Yes	Yes	Yes	Yes

Note. Columns 1 to 4 display the probability of logging in during the first to fourth weeks following the purchase of an stock (excluding non-business days and bank holidays). The dependent variable is a dummy equal to 1 when there is a login during the day. Only months in which no other transaction occurred after the purchase of the stock are included. The data is also restricted to months in which the cardholders has a portfolio of at least two stocks after the purchase. Change in value of the purchased stock is computed daily with respect of the value of that stock at the end of the purchase day. Change in value of the rest of the portfolio are measured with respect of the value during that day too. The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38; and for the number of stocks, Q1: 0.02 to 1.48, Q2: 1.48 to 3.11, Q3: 3.11 to 6.26, and Q4: 6.26 to 69.04 stocks. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

Table 4.8 Logins and Daily Returns, by Gains and Losses, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock + (Daily)	0.007***	0.003	0.005**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Purchased Stock - (Daily)	0.003	0.007***	0.003	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Remaining Stocks + (Daily)	0.005	0.005	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.002)
% Change, Remaining Stocks - (Daily	0.015***	0.016***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Female=1	-0.006	-0.008	0.002	0.000
	(0.014)	(0.013)	(0.013)	(0.013)
Investor Age				
28 - 37 years old	-0.040	-0.035	-0.046	-0.046
	(0.030)	(0.029)	(0.030)	(0.029)
38 - 47 years old	-0.017	-0.005	-0.006	-0.001
	(0.029)	(0.029)	(0.030)	(0.029)
48 - 57 years old	-0.009	0.003	0.001	0.014
	(0.029)	(0.028)	(0.029)	(0.028)
58 - 67 years old	0.011	0.027	0.023	0.033
	(0.030)	(0.029)	(0.031)	(0.030)
68 or more years old	0.047	0.064*	0.069*	0.078**
	(0.031)	(0.031)	(0.032)	(0.031)
Number of Trade Days per Month				
Quartile 2	0.074***	0.090***	0.080***	0.074***
	(0.016)	(0.015)	(0.015)	(0.014)
Quartile 3	0.169***	0.174***	0.167***	0.167***
	(0.015)	(0.015)	(0.014)	(0.014)
Quartile 4	0.306***	0.315***	0.299***	0.299***
	(0.016)	(0.015)	(0.016)	(0.016)
Portfolio Value				
Quartile 2	-0.022	-0.011	-0.001	-0.001
	(0.018)	(0.018)	(0.018)	(0.018)
Quartile 3	-0.001	0.006	0.021	0.019
	(0.019)	(0.018)	(0.018)	(0.018)
Quartile 4	0.006	0.020	0.031	0.028
	(0.020)	(0.019)	(0.020)	(0.020)
Number of Stocks				
Quartile 2	-0.017	-0.015	-0.028	-0.018
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 3	0.027	0.034	0.025	0.039
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 4	0.011	0.025	0.012	0.029
	(0.023)	(0.023)	(0.023)	(0.023)
Constant	0.331***	0.272***	0.244***	0.243***
	(0.080)	(0.085)	(0.069)	(0.071)
Observations	58280	58280	58284	58285
Number of Accounts	4669	4669	4670	4670
Adjusted R-squared	0.0608	0.0695	0.0686	0.0730
Region FE	Yes	Yes	Yes	Yes

Note. Columns 1 to 4 display the probability of logging in during the first to fourth weeks following the purchase of an stock (excluding non-business days and bank holidays). The dependent variable is a dummy equal to 1 when there is a login during the day. Only months in which no other transaction occurred after the purchase of the stock are included. The data is also restricted to months in which the cardholders has a portfolio of at least two stocks after the purchase. Change in value of the purchased stock and remaining stocks are computed daily with respect of the value in the previous business day. Change in value followed by a positive sign records the changes from 0; while change in value followed by a negative sign, up to 0 (excluding 0). The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38; and for the number of stocks, Q1: 0.02 to 1.48, Q2: 1.48 to 3.11, Q3: 3.11 to 6.26, and Q4: 6.26 to 69.04 stocks. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

Table 4.9 Logins and Returns Since Purchase, by Gains and Losses, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock + (Since Purchase)	0.002	0.002	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
% Change, Purchased Stock - (Since Purchase)	0.004***	0.002*	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
% Change, Remaining Stocks + (Since Purchase)	-0.000	0.004**	0.003	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
% Change, Remaining Stocks - (Since Purchase)	0.014***	0.007***	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
Female=1	-0.007	-0.007	0.002	0.000
	(0.014)	(0.013)	(0.013)	(0.013)
Investor Age				
28 - 37 years old	-0.039	-0.035	-0.047	-0.048
	(0.030)	(0.029)	(0.030)	(0.029)
38 - 47 years old	-0.015	-0.005	-0.007	-0.005
	(0.029)	(0.029)	(0.030)	(0.029)
48 - 57 years old	-0.008	0.003	0.000	0.011
	(0.029)	(0.028)	(0.029)	(0.028)
58 - 67 years old	0.012	0.026	0.022	0.030
	(0.030)	(0.029)	(0.031)	(0.030)
68 or more years old	0.048	0.064*	0.068*	0.075**
	(0.031)	(0.031)	(0.032)	(0.031)
Number of Trade Days per Month				
Quartile 2	0.075***	0.090***	0.080***	0.072***
	(0.016)	(0.015)	(0.015)	(0.014)
Quartile 3	0.170***	0.175***	0.168***	0.166***
	(0.015)	(0.015)	(0.014)	(0.014)
Quartile 4	0.308***	0.316***	0.302***	0.300***
	(0.016)	(0.015)	(0.016)	(0.016)
Portfolio Value				
Quartile 2	-0.023	-0.013	-0.005	-0.004
	(0.018)	(0.018)	(0.018)	(0.018)
Quartile 3	-0.002	0.004	0.018	0.015
	(0.019)	(0.018)	(0.018)	(0.018)
Quartile 4	0.003	0.016	0.025	0.022
	(0.020)	(0.019)	(0.020)	(0.019)
Number of Stocks				
Quartile 2	-0.018	-0.017	-0.029	-0.018
	(0.022)	(0.021)	(0.021)	(0.020)
Quartile 3	0.023	0.032	0.022	0.037
	(0.022)	(0.021)	(0.021)	(0.021)
Quartile 4	0.006	0.023	0.009	0.026
	(0.023)	(0.023)	(0.023)	(0.023)
Constant	0.345***	0.278***	0.260***	0.262***
	(0.080)	(0.085)	(0.070)	(0.072)
Observations	58280	58280	58280	58280
Number of Accounts	4669	4669	4669	4669
Adjusted R-squared	0.0618	0.0709	0.0706	0.0759
Region FE	Yes	Yes	Yes	Yes

Note. Columns 1 to 4 display the probability of logging in during the first to fourth weeks following the purchase of an stock (excluding non-business days and bank holidays). The dependent variable is a dummy equal to 1 when there is a login during the day. Only months in which no other transaction occurred after the purchase of the stock are included. The data is also restricted to months in which the cardholders has a portfolio of at least two stocks after the purchase. Change in value of the purchased stock is computed daily with respect of the value at the end of the purchase day. Change in value of the rest of the portfolio are measured with respect of the value during that day too. Change in value followed by a positive sign records the changes from 0; while change in value followed by a negative sign, up to 0 (excluding 0). The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38; and for the number of stocks, Q1: 0.02 to 1.48, Q2: 1.48 to 3.11, Q3: 3.11 to 6.26, and Q4: 6.26 to 69.04 stocks. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

4.5 Selective Attention II: Evidence from Weather Shocks

In this section, we exploit a second natural experiment in the data that allows us to examine the effects of changes in the opportunity cost of paying attention to the investment account. If paying attention is driven by hedonic utility, then attention to the investor's portfolio is a substitute for other forms of utility, such as leisure. Here, we exploit local level weather shocks as exogenous variation in the opportunity cost of time spent paying attention to the investor's portfolio (i.e., sitting at a computer and logging in to the investment account to read portfolio screens). A large literature examines the effect of the weather on stock prices (Hirshleifer and Shumway, 2003; Saunders, 1993). Our focus differs from that of those prior studies.

We construct measures of local level weather shocks using the postcode identifiers available in the Barclays data. We match investor locations (identified by postcode) to the nearest UK weather station and match data on daily weather patterns at each of the weather stations. To identify weather shocks, we exploit within-regional variation in the weather, i.e. variation within a UK region, as a source of exogenous change in the weather. The identifying assumption here is that investors cannot influence very local level weather. Our identification is based upon within-region variation. For example, weather may be sunny in the eastern region of the UK, but some areas within the eastern region nevertheless experience overcast weather.[8] To control for the effects of the weather on stock prices, we condition on day fixed effects. Hence, we exploit within-day within-region variation in the weather, controlling for regional weather patterns and daily stock prices. Of course, investors across different regions of the UK face the same stock market prices on a given day.

The weather data is constructed as follows. The Barclays data contain 2,846 unique postcodes, which represent the locations of investor home addresses. We match these to the 150 weather stations in the UK by geographic distance (based on the precise latitude and longitude of weather stations). Figure 4.6

[8] Although in the long-run investors might choose to move to places or regions with better weather, very local level weather is exogenous because investors' actions cannot influence local weather conditions.

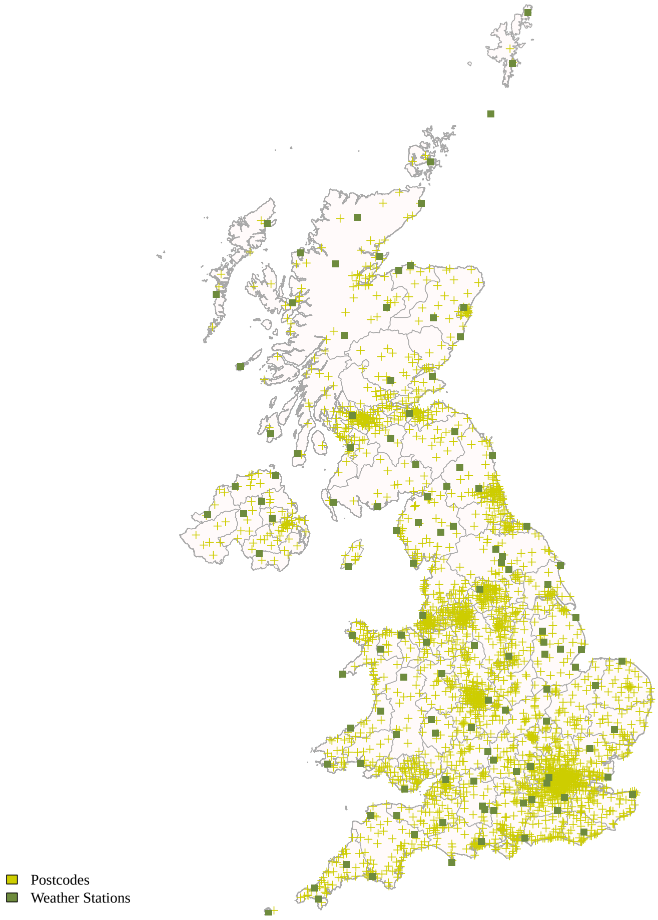


Fig. 4.6 Locations of UK weather stations. The figure shows the geographic location of UK weather stations (shown as dark green squares) and UK postcodes in the Barclays account data (light green crosses).

shows the geographic locations of weather stations and postcodes used in the matching exercise.[9] The match used 122 of the 150 weather stations.

Daily weather data was obtained for each weather station via the UK Open Data initiative.[10] Weather data is available at the hourly level. A daily measure of weather was constructed as the mode weather during daytime hours (8am

[9]This was implemented using the online tool available at https://www.doogal.co.uk/BatchGeocoding.php. Also, 79 postcodes in the Barclays data were corrupted and could not be matched.

[10]Met Office UK Weather open data is provided to https://data.gov.uk and hosted by Windows Azure Datamarket.

to 8pm), with weather measured as visibility range.[11] Figure 4.7 shows the within-day distribution of modal weather across localities in the dataset. As expected, modal weather in the winter months has more moderate, poor and very poor visibility, compared with summer months that are dominated by excellent and very good visibility.

We show the unconditional relationship between local weather and the logins in Figure 4.8. The figure illustrates a clear relationship that the probability of logging in on days with better visibility is lower, with a monotonic relationship across the categories of visibility. In Appendix C, in Figures C.2.1 to C.2.5, we show that this negative relationship between visibility and the probability of investors logging in holds across a range of variables. Figure C.2.1 shows this by gender, Figure C.2.2 shows that the relationship holds across different age groups in the data and Figure C.2.3 shows this by the frequency with which the investor trades within the month. Figure C.2.4 illustrates the same pattern by quartiles of portfolio value. Finally, Figure C.2.5 shows that the relationship between visibility and login behaviour is not driven by one particular season. The negative relationship is seen in all seasons.

These unconditional relationships suggest that investor attention is affected by the opportunity cost of logging in, but they do not control for investor characteristics or market prices. Therefore, in Table 4.10 we report estimates from regression models that quantify the relations described above controlling for investor and portfolio characteristics. The unit of analysis is an account $\times$ day, with the dependent variable being a dummy variable to indicate whether the investor logged in to his or her trading account on the day. We pool together all account $\times$ days in the baseline sample, providing 9.5 million observations. The likelihood of logging in on the day is then regressed against investor and portfolio controls, together with the measure of local weather. In Column 1, day fixed effects are added to the model. In Column 2, both day and region fixed effects are added, hence local weather is identified from within-day, within-region variation in the weather as discussed above.

[11] The visibility range measures are $>=$ 40000m, Excellent; $<$ 40000m, Very good; $<$ 20000m, Good; $<$ 10000m, Moderate; $<$ 4000m, Poor; and $<$ 1000m, Very poor. We combined the last two categories in one due to their low frequency.

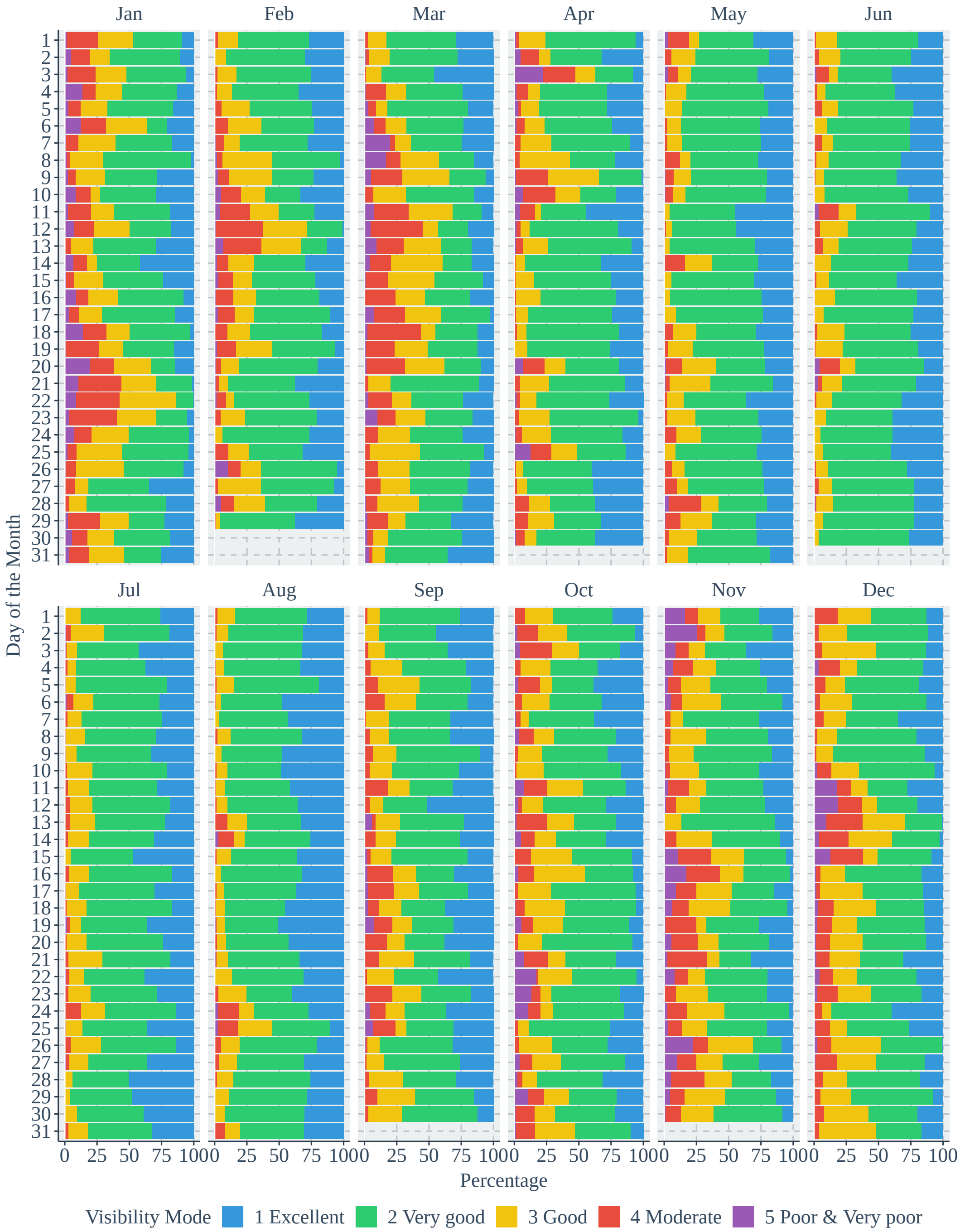


Fig. 4.7 Distribution of modal visibility across investor locations by calendar date. The plot shows the raw probability of the daytime visibility during the year. Data considers records of visibility during the period April 02,2012, to March 29, 2016.

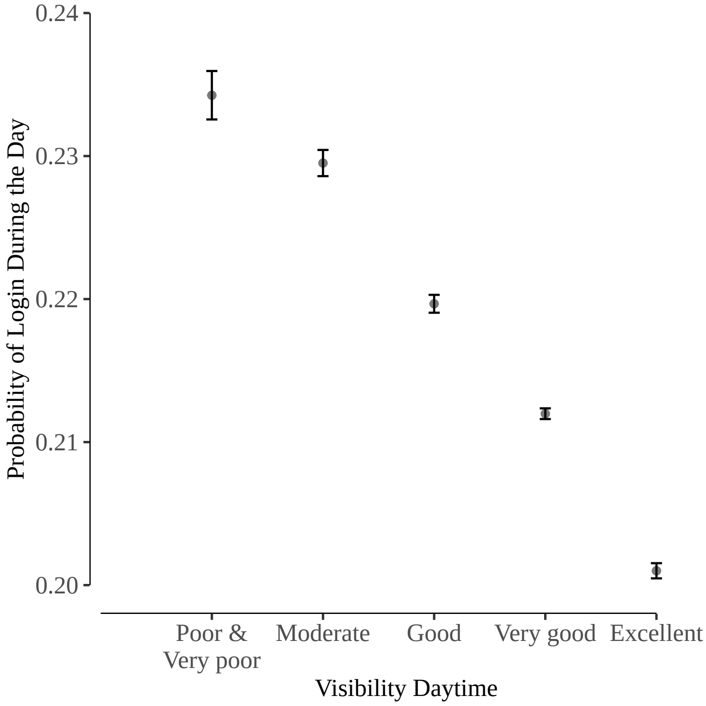


Fig. 4.8 Probability of logging in by daytime visibility. Lines span 95% confidence intervals.

Results show that investor attention is raised on days of poorer weather. The estimates in Column 1 imply that poor or very poor visibility increases the likelihood of logging in by 1 percentage point, an increase of approximately 5% of the baseline likelihood of logging in. With the addition of region fixed effects in Column 2, this coefficient reduces in magnitude to imply that poor or very poor visibility increases the likelihood of logging in by 0.8 percentage points. Other patterns in the coefficients resemble those from earlier estimates, with the probability of logging in lower among female investors and increasing with portfolio value and the number of trades undertaken each month.

These results are consistent with attention to the investor's portfolio being a substitute for other forms of utility, such as leisure. When the opportunity cost of taking the time to log in is high, i.e., on good weather days, the likelihood of investors taking the time to log in is lower. This naturally raises the question of whether the effects we see are driven by a particular type of investor. In particular, investors who log in very frequently might be more likely to defer their next login (temporarily) on sunny days.

Therefore, in additional analysis we replicate the main regression results across accounts by frequency of login. To do so, we partition the sample by quartile of the account level average distance between logins. We then conduct separate regressions on each subsample, controlling for investor and account characteristics as before. Coefficient estimates for the visibility variables are shown in Table 4.11. Results show that the relationship between weather and the probability of logging in exists only among the top quartile of accounts by login frequency, i.e., the quartile of accounts that log in most frequently. Coefficient estimates for this quartile are shown in Panel A, with statistically significant coefficients on each measure of visibility in both econometric model specifications. Results in Panels B–D show much smaller, or no, effects of visibility on the probability of logging in.

These estimates confirm that the effect of weather on investor attention behaviour arises from investors who logging in very frequently. This result fits with a hedonic utility based model of investor attention, in which investors who value the hedonic utility of seeing portfolio prices (those who logging in at highest frequency) are also those who are more likely to defer paying attention to their accounts when the opportunity cost of other forms of leisure is higher, such as on sunny days. Overall, these results are consistent with investor attention being driven by hedonic concerns.

Table 4.10 Logins and Daytime Visibility, Pooled OLS Models

	(1) Day FE	(2) Day & Region FE
Visibility Daytime		
(*ref: 1: Excellent*)		
Very good	0.003***	0.003***
	(0.000)	(0.000)
Good	0.006***	0.005***
	(0.000)	(0.000)
Moderate	0.005***	0.004***
	(0.001)	(0.001)
Poor & Very poor	0.010***	0.008***
	(0.001)	(0.001)
Female=1	-0.001***	-0.001***
	(0.000)	(0.000)
Age		
28 - 37 years old	-0.022***	-0.021***
	(0.001)	(0.001)
38 - 47 years old	-0.000	-0.000
	(0.001)	(0.001)
48 - 57 years old	0.023***	0.023***
	(0.001)	(0.001)
58 - 67 years old	0.060***	0.059***
	(0.001)	(0.001)
68 or more years old	0.071***	0.070***
	(0.001)	(0.001)
Portfolio Value		
Quartile 2	0.020***	0.020***
	(0.000)	(0.000)
Quartile 3	0.036***	0.037***
	(0.000)	(0.000)
Quartile 4	0.044***	0.045***
	(0.000)	(0.000)
Number of Trade Days per Month		
Quartile 2	0.038***	0.038***
	(0.000)	(0.000)
Quartile 3	0.111***	0.111***
	(0.000)	(0.000)
Quartile 4	0.250***	0.249***
	(0.000)	(0.000)
Investment in Mutual Funds = 1	0.035***	0.035***
	(0.000)	(0.000)
Number of Stocks	0.003***	0.003***
	(0.000)	(0.000)
Observations	9521825	9521825
Number of Accounts	8386	8386
Adjusted R-squared	0.1410	0.1417
Region FE	No	Yes
Day FE	Yes	Yes

Note. Visibility categories are defined based on the mode of the visibility during the time interval 8am to 8pm: excellent (visibility over 40,000 meters), very good (visibility less than 40,000 meters), good (visibility less than 20,000 meters), moderate (visibility less than 10,000 meters), and poor (visibility less than 4,000 metres). Portfolio value and number of stocks were measured at the first business day of the month. Quartiles represent the following values: for frequency of days with trades in a month, Q1: 0.04 to 0.13 days, Q2: 0.13 to 0.28 days, Q3: 0.28 to 0.62 days, and Q4: 0.62 to 17.90 days; and for the portfolio value (£1,000), Q1: 0.04 to 4.50, Q2: 4.51 to 15.21, Q3: 15.21 to 44.28, and 4 Q4: 44.28 to 2100.38. Standard errors in parentheses. Significance levels: *** p<0.01,** p<0.02, * p<0.05.

Table 4.11 Logins by Login Frequency, Pooled OLS Models

Panel A Quartile 1	(1) Day FE	(2) Day & Region FE
Very good	0.008***	0.006***
	(0.001)	(0.001)
Good	0.010***	0.006***
	(0.001)	(0.001)
Moderate	0.008***	0.006***
	(0.001)	(0.001)
Poor & Very poor	0.012***	0.010***
	(0.002)	(0.002)
Observations	2541142	2541142
Number of Accounts	2098	2098
Adjusted R-squared	0.2262	0.2270

Panel B Quartile 2	(1) Day FE	(2) Day & Region FE
Very good	0.001	0.000
	(0.001)	(0.001)
Good	0.001	0.001
	(0.001)	(0.001)
Moderate	0.003*	0.002
	(0.001)	(0.001)
Poor & Very poor	0.004*	0.003
	(0.002)	(0.002)
Observations	2418852	2418852
Number of Accounts	2096	2096
Adjusted R-squared	0.0594	0.0596

Panel C Quartile 3	(1) Day FE	(2) Day & Region FE
Very good	0.000	0.000
	(0.000)	(0.000)
Good	0.001*	0.001
	(0.001)	(0.001)
Moderate	0.002*	0.002
	(0.001)	(0.001)
Poor & Very poor	0.001	0.001
	(0.001)	(0.001)
Observations	2332152	2332152
Number of Accounts	2097	2097
Adjusted R-squared	0.0240	0.0240

Panel D Quartile 4	(1) Day FE	(2) Day & Region FE
Very good	-0.000	-0.000
	(0.000)	(0.000)
Good	0.001***	0.001***
	(0.000)	(0.000)
Moderate	0.002***	0.002***
	(0.001)	(0.001)
Poor & Very poor	0.002	0.002*
	(0.001)	(0.001)
Observations	2229679	2229679
Number of Accounts	2095	2095
Adjusted R-squared	0.0133	0.0133

Note. Quartiles defined based on the account average distance between login days. Standard errors in parentheses. Significance levels: *** p<0.01,** p<0.02, * p<0.05.

4.6 Conclusion

In this chapter, we study the allocation of attention to trading accounts by individual investors. Rich data from an online execution-only brokerage platform allows us to measure attention using logins to the platform. Consistent with previous studies, we find that investors log in to their accounts far more frequently than they trade, on average making a trade only once every nine logins. This suggests that investor attention to trading accounts is primarily driven by hedonic utility concerns, not by immediate trading needs.

We exploit two natural experiments which arise in the data to further explore whether attention is allocated in ways consistent with hedonic utility. First, we use short-term price movements in traded stocks to analyse the response of investor attention to losses and gains on recent purchases. Consistent with models of experienced loss aversion, we find that investors who experience losses on recent purchases are less likely to log in to their accounts in the period following. This result holds true for both thin and thick portfolios, and also extends to the weeks following the buy-trade.

Second, we use natural exogenous variation in the opportunity cost of time spent paying attention to the brokerage account arising from weather shocks. Matching data on local weather in the locality of the investor into the brokerage dataset, we estimate the effects of local level weather on login activity. Our econometric framework controls for region and day effects, holding constant prices on the specific day and exploiting within-region variation in local weather, which is arguably exogenous given that investors' actions cannot influence local weather conditions. Results show that investors are less likely to log in on sunny days, with this effect driven by investors who pay most attention to their accounts.

Taken together, our new results show that investor attention is sensitive to both the hedonic utility value of information (in the gain / loss domain) and the opportunity cost of alternative forms of utility, such as leisure. These results go some way to showing that individual investors do not allocate attention purely for the purpose of trading, but are susceptible to altering the level of attention in light of the changing hedonic utility value of experiences derived from logging in. These results contribute to the growing body of work in economics and psychology that focuses on the allocation of attention in a variety of financial settings.

Chapter 5

Conclusions

This thesis is a collection of three independent essays that investigate whether behavioral models of individual decision making find support in field data. Our approach has been to address questions about the psychology of decision making and behaviour using large datasets and the techniques from economics. Chapter 2 was devoted to the analysis of the effect of corrupting colleagues in police misconduct. Chapter 3 documented plain evidence of violations of fungibility in consumer credit card repayment choices. Chapter 4 revealed systematic patterns of information avoidance among investors. Our main findings can be briefly summarised as follows.

In Chapter 2, our main purpose was to investigate whether misconduct spreads among police officers: whether a bad apple would spoil the whole bunch. Our study builds on previous work that investigated peer influences in a variety of domains via both lab and field studies, such as absenteeism among school teachers, performance of batters and pitchers in baseball games, knowledge sharing among weavers, and so on (for a review, see Herbst and Mas, 2015). However, despite the abundant literature on peer effects on workers productivity, empirical studies of peer effects in police ethics and integrity have been often rare and the small amount of evidence available presents problems of inference that render their findings doubtful.

As we discussed in the first part of Chapter 2, quantifying peer effects is empirically challenging because of the endogeneity introduced when peers influence each other simultaneously and because there are common unobservable factors that affect the members of the same peer group and, therefore, mask genuine peer effects (Manski, 1993). To our knowledge, none of these challenges have been addressed convincingly in the police deviance literature and, as such, any study claiming causal peer effects has been premature in doing so. In Chapter 2, by using instrumental variable techniques, we overcame these challenges and reported non-trivial evidence of peer effects: a 10% increase in the fraction of peers with misconduct (e.g., when a complaint prone officer is transferred to an existing group of 10 officers) increases the officers' risk of misconduct by 8 percentage points. Our results are grounded on the analysis of large comprehensive datasets containing misconduct records for nearly fifty thousand police officers serving the UK Metropolitan Police during the period 2010 to 2015. We investigated peer effects when officers were assigned to different workgroups across these years; that is, our identification strategy exploited the variation in peer quality that officers experienced after they switched peer groups.

We should note that our results do not imply (or deny) the possibility that these effects occurred because officers learned from each other which behaviour is best to follow to satisfy their own interests or, instead perhaps, because they were corrupted by the pure peer pressure of their colleagues. Nor is our intention to engage in the discussion about which mechanisms have driven these peer influences. Nevertheless, it is quite reasonable to speculate that a large portion of these effects reveal evidence of social conformity. Notice that extensive qualitative research highlights that police culture is typically imbedded in unwritten rules and protected by a code of silence and extreme group loyalty (Loree, 2006). Moreover, its distinctive command-and-control style of management is alleged to promote close mutually supportive and inward-looking networks that preclude difference (Hough et al., 2018).

Having discussed peer influences, the second part of Chapter 2 is much more technical and address the question of whether misconduct can be deterred by sanctions. Evidence in the literature is inconclusive and, contrary to common sense, posits that more severe sanctions encourage deviance behaviour (Harris and Worden, 2014). We show, however, that this evidence is illusory and derives from testing the deterrent effects of sanctions ignoring individual heterogeneity. By studying a dynamic model that explicitly accounts for any individual (time invariant) difference among officers, we show that formal disciplinary actions do reduce future misconduct. Specifically, for officers with a history of complaints, formal disciplinary actions in the previous quarter reduces the chances of misconduct in the current quarter from 11.3% to 7.3%. Nonetheless, other sanction threats, such as management actions, do not appear to deter misconduct incidents.

The new findings provided here expand our understanding of the triggers that lead to police misconduct. Considering that integrity in policing is essential for stablishing and maintaining legitimacy and that the police disciplinary systems are grounded on the notion of deterrence, it is useful to have some quantitative sense of the size of the deterrent effect of each specific sanction type, as it is important too to have reliable measures of peer effects on deviant behaviour.

In addition to our main findings, there were a number of other findings that do not directly relate to the central questions of Chapter 2 but are summarized briefly next. Misconduct is most prominent among certain employee types, like police sergeants and constables. Male police officers and officers with few years of experience show a higher risk of misconduct. Although not statistically significant, we observed that those officers who worked with line manager that performed poorly (in their annual performance development reviews) evidenced a higher risk of misconduct too.

Some important limitations of the misconduct analysis above deserve consideration. Obviously, the major constraint of our two studies is the assumption that complaints filed against officers are accurate proxies of misconduct events. However, as we discussed in the final part of Chapter 2, these complaints could either over or under represent real misconduct events. On one hand, fellow officers, as opposed to citizens, might fail to report misconduct due to their cultural rules of integrity (Klockars et al., 1997; Wolfe and Piquero, 2011). Yet, it is also possible that those citizens who have low confidence in the complaint process might fail to report misconduct incidents too (Lersch, 2002). On the other hand, the frequency of complaints might mirror officers' productivity rather than actual deviant behaviour. In research of this nature, we are limited to the analysis of reported cases of misconduct taking them as factual. We note, however, that the study of allegations of misconduct is the usual approach adopted by the related literature and so no study in this domain have been immune to this constraint.

In Chapter 3, we move onto a different area and analyse how mental accounting rules influence intertemporal choices of credit card repayment. Specifically, we use a sample of 1.8 million credit card accounts to test a particular prediction of a theory of mental accounting proposed by Prelec and Loewenstein (1998): whether debt incurred on consumables is more likely to be paid off more rapidly than debt incurred on durables. The descriptive empirical results of Chapter 3 are strikingly clear. Repayment of debt incurred for non-durable goods is an absolute 10% more likely than repayment of debt incurred for durable goods. These results are the first field evidence in support for Prelec and Loewenstein's prediction. They challenge the normative view that people treat all money as fungible. If fungibility holds, what people pay for should not affect how they pay for it. We show, however, that people prefer to repay their different types of purchases in different ways, depending on the hedonic effects of both their future episodes of consumption and their future episodes of payments, as anticipated by Prelec and Loewenstein's double mental accounting model.

As we show in Appendix B, our results have passed a long list of robustness checks, such as alternative divisions of spending categories in durables and non-durables to the original one we tested and the inclusion of socioeconomic controls as well as controls for balances due on other cards held by the consumer at the same time. These additional checks show that repayment behaviour is driven by inter-temporal mental accounting rules but, to our surprise, they also show that repayment is driven by the application of intra-temporal heuristics. Specifically, in our data consumers holding multiple cards were more likely to pay down the card with the highest balance, instead of paying down the highest interest rate debt first, in consistency with the 'balance-matching' repayment heuristic proposed by Gathergood et al. (2017), in which consumers split the ratio of repayments across their cards in approximate proportion to the ratio of revolving balances. Gathergood et al. (2017) proposed this heuristic after analysing partial repayment of revolving debts, restricted to cases where consumers face interest payments; in contrast, in our analysis we restricted our data to observations where the consumers begin the month not revolving any debt (so that spending can be linked to repayment). Hence, by adding controls for the balances due on the other cards the consumers hold, we did not expect a priori evidence for the use of this heuristic. It is important to mention too that by the time our research went to peer-review, our main findings were replicated by Montgomery et al. (2018) using credit card data from a large U.S. bank which contains credit card transactions matched by household for more than 10,000 household units.

Although we did find consistent support for Prelec and Loewenstein's prediction, we could not rule out potential confounds common to the study of naturally occurring data. We were unable to account for selection into credit card spending for durable and non-durable goods, which might occur if some consumers were more likely to put onto their credit card spending on non-durable goods they intended to repay straightaway than spending on durable goods they intended to repay straightaway. Due to data constraints, we were also unable to account for other important determinants of repayment behaviour in which mental accounting might be relevant, such as the sources of income or the locations of funds cardholders use for repayment.

In our last chapter, we turn to discuss why and how traders pay selective attention to their portfolios. The study of investors' attention is economically important because the frequency with which investors monitor their portfolio limits the amount of information they could use for strategic decision making.

In Chapter 4, we assembled a rich panel dataset containing daily login records to online portfolio accounts and daily trading activity for a total of 155,309 accounts for a four-year period, starting from 2012. In our analysis, we extracted a representative random sample of 10% of accounts and reconstructed detailed portfolios for this sample. As such, we were able to define accurate measures of portfolio returns, contrary to earlier work on investors' attention that was limited to the analysis of correlations between login activity and some proxies of the investor expectations about their portfolio returns, such as the VIX index, the Dow index and the FTSE100 Index.

Our analysis of this data showed that investors log in to their accounts much more often than they trade. Logins appears to have a hedonic component over and above the purely functional procedure to make trades. This characteristic pattern of login activity allowed us to study selective attention. On one hand, we studied the demand side for attention and explored whether investors deliberately reduce their attention to negative news in order to evade the hedonic impact of those news in their utility function. On the other hand, we also examined the supply side for attention and evaluated how changes in the opportunity cost of attention affect investors' login activity. To this end, we exploited sub-regional variation within regions as the source of exogenous weather shocks that impact on the opportunity cost of attention.

After exploring the days following the purchase of a stock, we found that login activity is higher when the returns of that stock are higher and lower when the returns of that stock are lower. When investors anticipate that their portfolio has dropped in value, they appear to make attention decisions to regulate the hedonic pain of negative news. This pattern of behaviour remains stable even after controlling for several individual and portfolio characteristics. We also found that when the opportunity cost of attention is high (as it is in sunny days), investors tend to substitute viewing their portfolio for other less costly leisure activities. Thus, our general results suggest that investors treat attention as a hedonic activity, contrary to the normative view that the demand for attention (and so for information too) is only triggered by the investors wish to enhance their decision making.

Overall, the studies reported in this thesis show that individuals do not make decisions in isolation. Their choices reflect social and hedonic concerns. Their choices are heavily context dependent as well. While evidence showing how decision makers deviate from the normative rational ideal is prominent in lab studies, in order to attain generalizability of particular pieces of this evidence, we have opted to analyse naturally occurring observations and to test whether the results discovered in the lab extend to the field. The work in this PhD is part of a wider approach in the literature to address questions in psychological and behavioural science by combining newly available big data sets with the techniques from econometrics and, to the extent that we have been successful, illustrates the promise of such an approach.

We envision that our research can foster future work on the analysis of individual choice. There are some natural progressions for our studies. Regarding our investigation of deviant behaviour, one set of issues concerns why other disciplinary actions, rather than formal sanctions, have little to no deterrent effect and how these other actions could be enhanced to be more effective. The qualitative analysis of the mechanisms behind the peer effects are also of substantial interest. Concerning our work on the mental accounting of card repayment, future research could examine more closely how the double-entry mental accounting predictions interact with other mental accounting dimensions such as the location of funds or the sources of income. In addition, further research should be undertaken to quantify the economic impacts of selective attention on portfolio returns.

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Appendix A

Bad Cop, Bad Cops: Learning and Peer Effects on Police Misconduct

A.1 Fixed and Random Effects Estimates

Table A.1.1 presents results from panel models including both fixed and random effects that do not use instrumental variables. These panel models fit Equation 2.1 using all quarters in the data, even those in which peers never switch peer groups. While these panel models can be applied to the whole data set, they do not correct for endogeneity.

We find that the panel models show significant but small effects of peer misconduct. But our instrumental variable approach reveals that the panel models greatly underestimate the causal effect of peer misconduct.

Model 1 of Table A.1.1 shows the random effects (RE) estimates of Equation 2.1. We observe positive and statistically significant peer effects. Model 2 displays fixed effects (FE) estimates that account for any unobserved time invariant characteristic of the individuals. Although FE estimates are smaller in magnitude, they still exhibit the expected positive sign. Models 3 and 4 employ similar estimators but are restricted to the sample of individuals who had at least one incidence of misconduct in the period 2012 q1 to 2015 q1. There is no apparent variation in the size of the peer effects in this subset of the data. These preliminary results indicate that a 10-percentage point increase in the proportion of peers with cases of misconduct in $t-1$ would rise the rate of misconduct in t by between 0.17 (Model 2) to 0.66 (Model 1) percentage points. Although these results suggest that peer misconduct has some small negative spillover effects, part of these effects are potentially spurious because we have not yet accounted for endogeneity in the estimates.

Table 2.4 in the main text presents the estimates using our instrumental variable approach, which is critical for identifying the causal effect of peer misconduct. We observe that the estimated coefficients of peer effects in Table 2.4 are much larger to those found in the preceding panel models from Table A.1.1. A possible explanation for the large difference in the GMM estimates from Table 2.4 and the RE and FE estimates from Table A.1.1 is measurement errors in the endogenous variable $Peer\ y_{i,t-1}$, which will lead to attenuation bias in the RE and FE estimates (Cameron and Trivedi, 2005). Note that our endogenous variable represents the proportion of peers in $t-1$ with cases of misconduct and so measurement errors could arise if this proportion does not always capture all peers in $t-1$, probably because peers formally registered under certain line manager are only a subset of the actual peer group.

Hence, RE and FE estimates are subject to two sources of bias operating in opposite directions: the upward bias caused by endogeneity and correlated effects and the downward bias caused by measurement errors. If the endogenous variable is measured with error, our instruments are also subject to measurement error, as they represent the proportion of peers of peers with cases of misconduct. However, to the extent that the measurement errors in our instruments are uncorrelated with the measurement errors in the endogenous variable, our GMM estimator should correct both the endogeneity bias and the attenuation bias. Also, note that in contrast to the endogenous variable that measures the proportion of peers with misconduct of a single individual, our instruments, $\bar{P}1$ and $\bar{P}2$, constitute averages across many individuals and therefore should be subject to smaller measurement errors.

Table A.1.1 The Estimated Likelihood of Misconduct, Peer Effects

	Whole sample		Individuals with incidence of Misconduct	
	(1)	(2)	(3)	(4)
VARIABLES	RE	FE	RE	FE
Prop. of peers in $t-1$ with misconduct	0.066***	0.017***	0.063***	0.028***
	(0.005)	(0.005)	(0.007)	(0.008)
Gender (reference: Females)				
Male	0.015***		0.014***	
	(0.001)		(0.002)	
Employee type (reference: Civil Staff)				
Police Constable	0.032***		0.011***	
	(0.001)		(0.002)	
Police Sergeant	0.033***		0.012***	
	(0.002)		(0.003)	
Inspector	0.025***		0.001	
	(0.003)		(0.005)	
Chief Inspector, Superintendent, Chief Superintendent	0.010***		-0.017*	
	(0.003)		(0.008)	
Business Group (reference: TP - Boroughs East)				
TP - Boroughs North	-0.000		-0.000	
	(0.003)		(0.003)	
TP - Boroughs South	0.007**		0.008*	
	(0.002)		(0.003)	
TP - Boroughs West	0.001		0.003	
	(0.002)		(0.003)	
TP - Central	-0.040***		-0.058*	
	(0.006)		(0.029)	
TP - Criminal Justice & Crime	-0.010***		-0.005	
	(0.002)		(0.003)	
TP - Westminster	-0.001		-0.003	
	(0.004)		(0.005)	
Specialist Crime and Operations	-0.029***		-0.020***	
	(0.002)		(0.003)	
Specialist Operations	-0.045***		-0.032***	
	(0.002)		(0.003)	
Other Business Group	-0.036***		-0.026***	
	(0.002)		(0.005)	
Length of service				
Length of service (10 years)	-0.026***	-0.278***	-0.018***	-0.657***
	(0.002)	(0.043)	(0.005)	(0.101)
Length of service (10 years)^2	0.004***	0.009***	0.004**	0.027***
	(0.001)	(0.003)	(0.001)	(0.008)
Employee Rating in $t-4$ (reference: Competent but development required + Not Yet Competent)				
Exceptional + Competent (above standard)	-0.035***	-0.010	-0.035***	-0.019
	(0.005)	(0.007)	(0.009)	(0.013)
Competent (at required standard)	-0.028***	-0.010	-0.030***	-0.018
	(0.005)	(0.007)	(0.009)	(0.013)
Constant	0.078***	0.451***	0.119***	0.944***
	(0.006)	(0.066)	(0.010)	(0.136)
Observations	331,023	331,022	141,074	141,073
Number of individuals	35,924	35,923	14,853	14,852
R-squared		0.001		0.002
ICC	0.0235		0	
σ_u	0.0329		0	
Quarter FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES

Note. All models estimate the probability of at least one event of misconduct in quarter t conditional on a set of covariates. The variable of interest is the proportion of peers in quarter $t-1$ with reported cases of misconduct. Columns 1 to 4 are linear probability panel data models that ignore the endogeneity in the peer misconduct measure. RE estimators in Columns 1 and 3 incorporate random individual intercepts that are assumed to be uncorrelated with the explanatory variables. RE estimators use information from both between individual variation and within individual variation in the data. However, FE estimators in Columns 2 and 4 use only within individual variation in the data. Thus, time-invariant characteristics in our data, like gender, employee type or business groups, cannot be estimated by FE models. By using only within individual variation, FE estimators allow for correlations between the individual intercepts and the explanatory variables. Alternative specifications applying instrumental variable techniques for the identification of peer effects are presented in Table 2.4 in the main text. Standard errors in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05,   p<0.10.

A.2 Peer Effects on the Likelihood of Misconduct - First Stage GMM

Table A.2.1 Peer Effects on the Likelihood of Misconduct - First Stage GMM

	Individuals experiencing new peers
	(1)
VARIABLES	GMM
Instrument 1	0.048***
	(0.004)
Instrument 2	0.028***
	(0.004)
Gender (reference: Females)	0.003***
Male	(0.001)
Employee type (reference: Civil Staff)	
Police Constable	0.022***
	(0.001)
Police Sergeant	0.020***
	(0.001)
Inspector	0.016***
	(0.002)
Chief Inspector, Superintendent, Chief Superintendent	-0.001
	(0.003)
Business Group (reference: Territorial Police (TP) - Boroughs East)	
TP - Boroughs North	0.000
	(0.002)
TP - Boroughs South	0.002
	(0.002)
TP - Boroughs West	-0.002
	(0.002)
TP - Central	-0.018~
	(0.011)
TP - Criminal Justice & Crime	-0.013***
	(0.002)
TP - Westminster	0.000
	(0.003)
Specialist Crime and Operations	-0.025***
	(0.001)
Specialist Operations	-0.039***
	(0.002)
Other Business Group	-0.039***
	(0.002)
Length of service	
Length of service (10 years)	-0.022***
	(0.002)
Length of service (10 years)^2	0.004***
	(0.001)
Employee Rating in $t-4$ (reference: Competent but development required + Not Yet Competent)	
Exceptional + Competent (above standard)	-0.012*
	(0.005)
Competent (at required standard)	-0.005
	(0.005)
Constant	0.079***
	(0.005)
Observations	80,632
Number of individuals	30,627
LM test statistic for under identification (Kleibergen-Paap)	199.3
P-value of under identification LM statistic	P <0.001
F statistic for weak identification (Kleibergen-Paap)	97.75
Quarter FEs	YES
Year FEs	YES

Note. The regression displays the first stage results of Model 1 in Table 2.4. The dependent variable is the proportion of peers in quarter $t-1$ with reported cases of misconduct. Two instruments are used for identification: the average proportion of peers of peers with incidence of misconduct in $t-2$ and, likewise, the average proportion of peers of peers with incidence of misconduct in $t-3$. Standard errors clustered by individuals in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05,   p<0.10.

Appendix B

The Red, the Black, and the Plastic: Paying Down Credit Card Debt for Hotels not Sofas

B.1 Descriptive Statistics of Purchase Amounts for all Accounts

Table B.1.1 Descriptive Statistics of Purchase Amounts for All Accounts – Single-Purchase-Type Samples

	Frequency	Mean	SD	p25	p50	p75
Non-durables						
Airlines	3310	£687.28	£896.29	£171.26	£376.17	£843.81
Auto Rental	1699	£232.90	£653.84	£65.95	£125.00	£248.81
Hotel/Motel	6428	£352.50	£604.42	£84.00	£175.88	£385.51
Restaurants/Bars	4588	£158.61	£546.68	£30.00	£59.28	£116.47
Travel Agencies	7509	£1,057.38	£1,138.03	£257.10	£680.22	£1,449.66
Other Transportation	3980	£314.42	£756.31	£34.90	£82.12	£250.00
Drug Stores	905	£54.92	£117.79	£16.00	£32.95	£59.99
Gas Stations	7570	£73.01	£207.80	£32.72	£49.31	£68.96
Mail Orders	13682	£110.09	£227.94	£23.00	£49.99	£121.31
Food Stores	14920	£88.22	£206.36	£24.00	£49.50	£96.61
Other Retail	17528	£180.00	£568.35	£19.46	£43.95	£118.38
Recreation	5774	£255.34	£513.93	£50.75	£109.61	£246.00
Subtotal	87893	£260.65	£627.71	£30.30	£68.83	£199.00
Durables						
Department Stores	3629	£239.77	£560.15	£39.99	£84.00	£228.95
Discount Stores	1704	£166.09	£218.47	£45.91	£101.41	£225.99
Clothing Stores	8939	£122.45	£217.56	£33.99	£61.19	£122.95
Hardware Stores	5022	£434.42	£1,048.35	£34.95	£89.99	£301.59
Vehicles	5894	£880.63	£1,569.33	£135.00	£285.00	£698.54
Interior Furnishing Stores	4493	£671.81	£998.71	£112.88	£330.00	£805.57
Electric Appliance Stores	6169	£384.74	£566.86	£59.99	£247.98	£460.76
Sporting Goods/Toy Stores	2886	£245.67	£797.44	£38.20	£79.99	£199.99
Health Care	3164	£441.70	£895.00	£66.88	£165.00	£347.10
Education	744	£715.45	£1,195.68	£61.28	£206.00	£866.00
Professional Services	12791	£311.76	£529.87	£68.88	£187.70	£346.47
Repair Shops	122	£314.43	£646.86	£34.67	£79.00	£299.00
Other Services	11474	£386.89	£972.88	£30.00	£89.84	£274.50
Subtotal	67031	£389.61	£871.30	£45.98	£132.00	£348.30
Single purchase total	154924	£316.45	£745.71	£36.00	£89.74	£265.75

Note. Single purchase total shows the monthly spending for the Single-Purchase-Type Sample of monthly observations belonging to all credit card accounts. SD=standard deviation. p25=25th percentile, p50=median, and p75=75th percentile.

Table B.1.2 Descriptive Statistics of Purchase Amounts for All Accounts – Multiple-Purchase-Type Sample

	Frequency	Mean	SD	p25	p50	p75
Non-durables						
Airlines	9140	£913.88	£994.19	£277.80	£580.07	£1,198.82
Auto Rental	5275	£627.96	£859.00	£149.16	£348.09	£771.60
Hotel/Motel	23202	£658.96	£807.45	£180.30	£397.79	£818.73
Restaurants/Bars	34714	£591.75	£777.08	£136.69	£338.51	£749.61
Travel Agencies	16807	£1,091.29	£1,111.30	£329.68	£737.39	£1,470.14
Other Transportation	18705	£607.33	£835.77	£122.93	£325.31	£748.73
Drug Stores	11347	£611.50	£761.65	£129.84	£359.88	£802.15
Gas Stations	38893	£512.97	£721.04	£90.89	£264.15	£643.15
Mail Orders	29807	£314.29	£567.46	£41.70	£119.88	£335.86
Food Stores	65526	£451.56	£679.03	£81.04	£219.79	£540.19
Other Retail	66961	£468.18	£751.61	£67.31	£213.30	£552.47
Recreation	21587	£584.19	£769.27	£132.00	£322.13	£735.25
Subtotal	201729	£416.22	£717.53	£60.00	£169.10	£455.08
Durables						
Department Stores	19045	£610.54	£823.67	£128.49	£329.46	£760.78
Discount Stores	9664	£586.99	£718.87	£144.99	£349.99	£749.97
Clothing Stores	43212	£495.36	£682.22	£98.37	£252.84	£609.98
Hardware Stores	21944	£699.69	£1,018.36	£118.86	£342.14	£848.62
Vehicles	16170	£895.12	£1,282.45	£206.01	£449.56	£1,000.00
Interior Furnishing Stores	16900	£859.11	£1,062.17	£210.54	£510.21	£1,089.32
Electric Appliance Stores	19460	£661.94	£876.12	£158.60	£388.00	£807.61
Sporting Goods/Toy Stores	14928	£600.04	£808.47	£127.46	£338.58	£760.22
Health Care	9508	£628.08	£907.03	£145.73	£318.37	£694.78
Education	2388	£781.05	£1,031.59	£152.49	£429.24	£1,019.88
Professional Services	28118	£559.69	£805.32	£131.45	£301.72	£648.93
Repair Shops	601	£733.74	£927.61	£140.65	£379.79	£965.40
Other Services	38198	£621.45	£956.66	£100.70	£294.24	£740.43
Subtotal	163269	£511.69	£845.92	£90.94	£241.08	£560.00
Multiple purchases total	282997	£418.52	£768.13	£58.17	£164.95	£437.83

Note. Multiple purchase total shows the monthly spending for the Multiple-Purchase-Type Sample of monthly observations belonging to all credit card accounts. Note that the Multiple-Purchase-Type Sample includes the Single-Purchase-Type Sample described in Table B.1.1. As cardholders can consume products in more than one category during the month, frequencies for each category do not add to the month observations displayed in the multiple purchases total. SD=standard deviation. p25=25th percentile, p50=median, and p75=75th percentile.

B.2 Regressions with additional controls

Table B.2.1 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable = 1	0.193***	0.0920***	0.0909***	0.0386***	0.135***	0.0864***	0.0450***
	(0.00801)	(0.00690)	(0.00682)	(0.0100)	(0.0157)	(0.0176)	(0.0125)
Merchant APR (%)			0.00547***	0.00290***	0.00680***	0.00799***	0.00838***
			(0.000386)	(0.000521)	(0.000887)	(0.00103)	(0.000886)
Credit limit (£1000)			0.00150	0.000252	0.00363	0.000941	-0.00955*
			(0.00151)	(0.00223)	(0.00352)	(0.00456)	(0.00490)
Utilization (%)			-0.00192***	-0.00868***	-0.00244**	-0.00272***	-0.00181***
			(0.000271)	(0.00260)	(0.00119)	(0.000565)	(0.000486)
Account age (years)			0.116***	-0.00467	0.159***	0.262***	0.277***
			(0.0147)	(0.0190)	(0.0342)	(0.0384)	(0.0337)
Amount purchase (£1000)		-1.046***	-0.916***	17.21	5.127	-73.35**	-0.221**
		(0.0211)	(0.0252)	(14.80)	(74.59)	(37.36)	(0.0944)
Amount purchase $(£1000)^2$		0.475***	0.432***	-942.3	-30.40	266.0*	0.0767*
		(0.0157)	(0.0161)	(950.7)	(910.1)	(137.4)	(0.0412)
Amount purchase $(£1000)^3$		-0.0884***	-0.0812***	22,639	-147.7	-466.7*	-0.0110
		(0.00393)	(0.00395)	(26,754)	(5,337)	(244.3)	(0.00764)
Amount purchase $(£1000)^4$		0.00700***	0.00645***	-261,099	1,342	395.7*	0.000711
		(0.000381)	(0.000380)	(339,801)	(15,086)	(210.6)	(0.000612)
Amount purchase $(£1000)^5$		-0.000194***	-0.000179***	1.148×10^{6}	-2,353	-130.0*	-1.72×10^{-5}
		(1.22×10^{-5})	(1.22×10^{-5})	(1.592×10^{6})	(16,496)	(70.50)	(1.73×10^{-5})
Median house price (£)	1.30×10^{-7}**	3.31×10^{-8}	2.76×10^{-8}	-1.44×10^{-7}*	4.61×10^{-8}	1.55×10^{-7}	2.33×10^{-7}**
	(6.55×10^{-8})	(5.52×10^{-8})	(5.46×10^{-8})	(7.79×10^{-8})	(1.20×10^{-7})	(1.41×10^{-7})	(1.07×10^{-7})
Free school meals (proportion)	-0.297***	-0.290***	-0.274***	-0.243***	-0.228*	-0.395***	-0.266**
	(0.0702)	(0.0592)	(0.0587)	(0.0826)	(0.136)	(0.152)	(0.108)
Weekly Household Income (£)	-7.71×10^{-5}	-1.86×10^{-5}	-1.01×10^{-5}	8.67×10^{-6}	5.13×10^{-5}	-4.55×10^{-5}	-0.000123
	(4.98×10^{-5})	(4.20×10^{-5})	(4.15×10^{-5})	(5.87×10^{-5})	(9.48×10^{-5})	(0.000107)	(7.91×10^{-5})
Constant	0.530***	0.826***	0.763***	0.781***	0.463	8.219**	0.430***
	(0.0342)	(0.0291)	(0.0340)	(0.0919)	(2.347)	(3.926)	(0.0976)
Observations	14,851	14,851	14,851	5,677	3,662	2,777	2,735
Observations Non-durable = 1	8,029	8,029	8,029	3,817	1,906	1,115	1,191
R-squared	0.039	0.317	0.335	0.031	0.080	0.101	0.111
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.2.1 replicates Table 3.4 specifications with the addition of socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to only one spending type. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.2.2 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable (proportion)	0.234***	0.144***	0.142***	0.0413***	0.158***	0.209***	0.119***
	(0.00598)	(0.00546)	(0.00539)	(0.00932)	(0.0113)	(0.0112)	(0.00996)
Merchant APR (%)			0.00613***	0.00334***	0.00576***	0.00722***	0.00816***
			(0.000278)	(0.000455)	(0.000533)	(0.000584)	(0.000694)
Credit limit (£1000)			0.00582***	0.00254	0.00801***	0.0105***	0.00413
			(0.00109)	(0.00198)	(0.00222)	(0.00229)	(0.00297)
Utilization (%)			-0.00202***	-0.00544***	-0.00126*	-0.00188***	-0.00157***
			(0.000175)	(0.00206)	(0.000657)	(0.000310)	(0.000321)
Account age (years)			0.146***	0.00657	0.148***	0.239***	0.270***
			(0.0115)	(0.0169)	(0.0228)	(0.0248)	(0.0287)
Amount purchase (£1000)		-0.885***	-0.726***	11.02	85.40*	-5.885	-0.183***
		(0.0143)	(0.0169)	(13.60)	(45.01)	(18.56)	(0.0702)
Amount purchase (£1000)^2		0.412***	0.347***	-561.1	-1,051*	24.16	0.0521
		(0.0110)	(0.0113)	(854.6)	(544.3)	(67.89)	(0.0323)
Amount purchase (£1000)^3		-0.0801***	-0.0680***	12,078	6,110*	-48.83	-0.00702
		(0.00289)	(0.00290)	(23,594)	(3,165)	(120.1)	(0.00625)
Amount purchase (£1000)^4		0.00662***	0.00563***	-127,313	-17,052*	46.25	0.000464
		(0.000292)	(0.000291)	(294,754)	(8,875)	(102.9)	(0.000519)
Amount purchase (£1000)^5		-0.000190***	-0.000162***	519,083	18,397*	-16.47	-1.21x10^{-5}
		(9.69x10^{-6})	(9.63x10^{-6})	(1.361x10^{6})	(9,633)	(34.27)	(1.51x10^{-5})
Median house price (£)	1.85x10^{-7}***	1.19x10^{-7}***	1.06x10^{-7}***	-8.48x10^{-8}	1.99x10^{-7}***	1.21x10^{-7}*	1.25x10^{-7}*
	(3.95x10^{-8})	(3.55x10^{-8})	(3.50x10^{-8})	(6.94x10^{-8})	(7.34x10^{-8})	(6.29x10^{-8})	(6.82x10^{-8})
Free school meals (proportion)	-0.239***	-0.331***	-0.298***	-0.229***	-0.320***	-0.244***	-0.434***
	(0.0440)	(0.0395)	(0.0391)	(0.0713)	(0.0802)	(0.0765)	(0.0747)
Weekly Household Income (£)	-4.34x10^{-5}	3.85x10^{-5}	3.91x10^{-5}	-2.29x10^{-5}	-9.16x10^{-6}	0.000115**	5.08x10^{-5}
	(3.03x10^{-5})	(2.72x10^{-5})	(2.68x10^{-5})	(5.15x10^{-5})	(5.67x10^{-5})	(5.02x10^{-5})	(5.05x10^{-5})
Constant	0.397***	0.703***	0.592***	0.809***	-2.099	0.791	0.277***
	(0.0212)	(0.0194)	(0.0226)	(0.0842)	(1.429)	(1.959)	(0.0663)
Observations	38,481	38,481	38,481	7,854	10,440	11,741	8,446
R-squared	0.041	0.227	0.250	0.030	0.062	0.094	0.102
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.2.2 replicates Table 3.5 specifications but including socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to one or more purchase types. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B.3 Reclassification of Consumption Categories

Table B.3.1 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £59.93)	OLS – Quartile 2 (Q2: £59.94 - £229.00)	OLS – Quartile 3 (Q3: £229.01 - £884.40)	OLS – Quartile 4 (£884.41 - £17000)
Non-durable = 1	0.122***	0.0704***	0.0722***	0.0229**	0.109***	0.0962***	0.0353***
	(0.00688)	(0.00574)	(0.00568)	(0.00919)	(0.0125)	(0.0130)	(0.00906)
Merchant APR (%)			0.00622***	0.00297***	0.00646***	0.00882***	0.00862***
			(0.000344)	(0.000500)	(0.000715)	(0.000834)	(0.000744)
Credit limit (£1000)			0.00257**	-0.00110	0.00538*	0.00416	-0.000140
			(0.00129)	(0.00213)	(0.00279)	(0.00336)	(0.00361)
Utilization (%)			-0.00156***	-0.00883***	-0.00279**	-0.00230***	-0.000824**
			(0.000218)	(0.00311)	(0.00117)	(0.000445)	(0.000344)
Account age (years)			0.127***	0.00511	0.0969***	0.282***	0.304***
			(0.0124)	(0.0177)	(0.0257)	(0.0296)	(0.0259)
Amount purchase (£1000)		-1.070***	-0.950***	27.76	-81.11	-20.15	-0.246***
		(0.0161)	(0.0196)	(25.66)	(56.63)	(16.31)	(0.0602)
Amount purchase $(£1000)^2$		0.479***	0.439***	-1,620	1,228	73.34	0.0851***
		(0.0114)	(0.0117)	(2,081)	(906.7)	(67.72)	(0.0256)
Amount purchase $(£1000)^3$		-0.0864***	-0.0797***	43,749	-9,084	-131.0	-0.0128***
		(0.00272)	(0.00273)	(75,445)	(6,935)	(134.4)	(0.00458)
Amount purchase $(£1000)^4$		0.00655***	0.00606***	-606,983	32,210	113.1	0.000862**
		(0.000251)	(0.000250)	($1.251x10^6$)	(25,434)	(128.0)	(0.000352)
Amount purchase $(£1000)^5$		-0.000173***	-0.000160***	$3.467x10^6$	-43,884	-37.88	$-2.10x10^{-5}$**
		($7.66x10^{-6}$)	($7.62x10^{-6}$)	($7.715x10^6$)	(35,931)	(46.99)	($9.53x10^{-6}$)
Constant	0.455***	0.776***	0.696***	0.685***	2.728**	2.417	0.300***
	(0.00533)	(0.00559)	(0.0160)	(0.113)	(1.348)	(1.500)	(0.0529)
Observations	21,671	21,671	21,671	6,151	5,922	4,961	4,637
Observations Non-durable = 1	13,027	13,027	13,027	3,991	3,758	2,802	2,476
R-squared	0.014	0.321	0.340	0.022	0.065	0.105	0.104
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. The sample is restricted to new accounts and includes months in which expenses were related to only one purchase type. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £59.93. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.3.2 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £59.93)	OLS – Quartile 2 (Q2: £59.94 - £229.00)	OLS – Quartile 3 (Q3: £229.01 - £884.40)	OLS – Quartile 4 (£884.41 - £17000)
Non-durable = 1	0.110***	0.0643***	0.0660***	0.0183*	0.105***	0.0798***	0.0377***
	(0.00826)	(0.00693)	(0.00686)	(0.0104)	(0.0146)	(0.0163)	(0.0123)
Merchant APR (%)			0.00556***	0.00274***	0.00582***	0.00854***	0.00799***
			(0.000387)	(0.000554)	(0.000800)	(0.000960)	(0.000876)
Credit limit (£1000)			0.00170	-0.000404	0.00305	0.00284	-0.00876*
			(0.00152)	(0.00244)	(0.00319)	(0.00410)	(0.00481)
Utilization (%)			-0.00196***	-0.0118***	-0.00306**	-0.00268***	-0.00179***
			(0.000272)	(0.00363)	(0.00136)	(0.000551)	(0.000478)
Account age (years)			0.115***	-0.00729	0.0960***	0.266***	0.285***
			(0.0147)	(0.0202)	(0.0301)	(0.0365)	(0.0331)
Amount purchase (£1000)		-1.085***	-0.951***	30.86	-107.4	-15.11	-0.185**
		(0.0209)	(0.0251)	(28.70)	(66.75)	(20.58)	(0.0904)
Amount purchase (£1000)^2		0.499***	0.455***	-2,203	1,701	52.34	0.0637
		(0.0156)	(0.0160)	(2,338)	(1,071)	(85.61)	(0.0399)
Amount purchase (£1000)^3		-0.0938***	-0.0864***	73,411	-13,019	-88.57	-0.00903
		(0.00392)	(0.00393)	(85,075)	(8,204)	(170.3)	(0.00746)
Amount purchase (£1000)^4		0.00747***	0.00690***	-1.175x10^{6}	47,506	71.85	0.000585
		(0.000380)	(0.000379)	(1.414x10^{6})	(30,138)	(162.5)	(0.000601)
Amount purchase (£1000)^5		-0.000208***	-0.000193***	7.172x10^{6}	-66,317	-22.40	-1.43x10^{-5}
		(1.22x10^{-5})	(1.21x10^{-5})	(8.744x10^{6})	(42,646)	(59.75)	(1.71x10^{-5})
Median house price (£)	1.22x10^{-7}*	2.83x10^{-8}	2.34x10^{-8}	-1.30x10^{-7}	-1.83x10^{-8}	1.45x10^{-7}	2.26x10^{-7}**
	(6.64x10^{-8})	(5.54x10^{-8})	(5.47x10^{-8})	(8.08x10^{-8})	(1.16x10^{-7})	(1.28x10^{-7})	(1.07x10^{-7})
Free school meals (proportion)	-0.296***	-0.290***	-0.273***	-0.330***	-0.145	-0.339**	-0.294***
	(0.0711)	(0.0594)	(0.0588)	(0.0885)	(0.123)	(0.142)	(0.107)
Weekly Household Income (£)	-6.46x10^{-5}	-1.33x10^{-5}	-5.32x10^{-6}	-4.09x10^{-5}	0.000121	-4.37x10^{-5}	-0.000134*
	(5.05x10^{-5})	(4.21x10^{-5})	(4.16x10^{-5})	(6.18x10^{-5})	(8.70x10^{-5})	(0.000100)	(7.85x10^{-5})
Constant	0.561***	0.842***	0.775***	0.794***	3.257**	2.059	0.462***
	(0.0347)	(0.0292)	(0.0341)	(0.133)	(1.587)	(1.889)	(0.0928)
Observations	14,851	14,851	14,851	4,581	4,150	3,284	2,836
Observations Non-durable = 1	8,934	8,934	8,934	2,950	2,605	1,854	1,525
R-squared	0.014	0.313	0.331	0.023	0.069	0.104	0.108
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.3.2 replicates Table B.3.1 specifications with the addition of socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to only one purchase type. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £59.93. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.3.3 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £59.93)	OLS – Quartile 2 (Q2: £59.94 - £229.00)	OLS – Quartile 3 (Q3: £229.01 - £884.40)	OLS – Quartile 4 (£884.41 - £17000)
Non-durable (proportion)	0.162***	0.112***	0.112***	0.0183**	0.126***	0.174***	0.0726***
	(0.00504)	(0.00454)	(0.00448)	(0.00867)	(0.00951)	(0.00858)	(0.00760)
Merchant APR (%)			0.00699***	0.00314***	0.00618***	0.00813***	0.00868***
			(0.000251)	(0.000450)	(0.000467)	(0.000477)	(0.000612)
Credit limit (£1000)			0.00759***	-0.000519	0.00758***	0.0133***	0.00719***
			(0.000918)	(0.00193)	(0.00186)	(0.00173)	(0.00226)
Utilization (%)			-0.00207***	-0.00929***	-0.00237***	-0.00186***	-0.00150***
			(0.000140)	(0.00259)	(0.000661)	(0.000242)	(0.000238)
Account age (years)			0.142***	0.0108	0.0981***	0.208***	0.261***
			(0.00980)	(0.0160)	(0.0186)	(0.0192)	(0.0228)
Amount purchase (£1000)		-0.886***	-0.723***	14.40	-89.06**	-12.04	-0.213***
		(0.0111)	(0.0132)	(23.98)	(37.90)	(8.117)	(0.0469)
Amount purchase $(£1000)^2$		0.406***	0.341***	-646.1	1,344**	48.35	0.0636***
		(0.00821)	(0.00841)	(1,916)	(598.4)	(33.51)	(0.0213)
Amount purchase $(£1000)^3$		-0.0768***	-0.0648***	12,588	-9,928**	-96.10	-0.00899**
		(0.00208)	(0.00208)	(68,577)	(4,518)	(66.19)	(0.00403)
Amount purchase $(£1000)^4$		0.00610***	0.00516***	-148,006	35,407**	91.63	0.000603*
		(0.000201)	(0.000200)	$(1.124\text{x}10^{6})$	(16,379)	(62.77)	(0.000325)
Amount purchase $(£1000)^5$		-0.000167***	-0.000142***	914,844	-48,778**	-33.45	$-1.52\text{x}10^{-5}$*
		$(6.38\text{x}10^{-6})$	$(6.33\text{x}10^{-6})$	$(6.864\text{x}10^{6})$	(22,904)	(22.95)	$(9.11\text{x}10^{-6})$
Constant	0.371***	0.709***	0.594***	0.741***	2.877***	1.456*	0.312***
	(0.00367)	(0.00446)	(0.0107)	(0.107)	(0.916)	(0.751)	(0.0385)
Observations	58,404	58,404	58,404	7,890	14,423	21,312	14,779
R-squared	0.017	0.212	0.238	0.022	0.052	0.081	0.078
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.3.3 replicates Table B.3.1 specifications but months with multiple consumption categories or merchant codes are added to the sample. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £59.93. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.3.4 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts, Additional Controlss

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £59.93)	OLS – Quartile 2 (Q2: £59.94 - £229.00)	OLS – Quartile 3 (Q3: £229.01 - £884.40)	OLS – Quartile 4 (£884.41 - £17000)
Non-durable (proportion)	0.148***	0.101***	0.102***	0.0127	0.121***	0.153***	0.0789***
	(0.00619)	(0.00555)	(0.00548)	(0.00987)	(0.0112)	(0.0107)	(0.00998)
Merchant APR (%)			0.00616***	0.00287***	0.00528***	0.00731***	0.00813***
			(0.000279)	(0.000499)	(0.000517)	(0.000536)	(0.000685)
Credit limit (£1000)			0.00594***	3.38×10^{-5}	0.00664***	0.0112***	0.00298
			(0.00110)	(0.00222)	(0.00218)	(0.00213)	(0.00289)
Utilization (%)			-0.00210***	-0.0112***	-0.00183**	-0.00189***	-0.00176***
			(0.000176)	(0.00308)	(0.000804)	(0.000305)	(0.000314)
Account age (years)			0.143***	-0.00509	0.104***	0.230***	0.278***
			(0.0116)	(0.0184)	(0.0215)	(0.0230)	(0.0283)
Amount purchase (£1000)		-0.920***	-0.756***	14.90	-97.26**	-10.75	-0.209***
		(0.0143)	(0.0169)	(26.85)	(44.48)	(10.25)	(0.0668)
Amount purchase $(£1000)^2$		0.432***	0.366***	-963.1	1,490**	39.82	0.0652**
		(0.0110)	(0.0113)	(2,155)	(703.6)	(42.42)	(0.0312)
Amount purchase $(£1000)^3$		-0.0846***	-0.0722***	30,133	-11,120**	-72.86	-0.00968
		(0.00290)	(0.00291)	(77,381)	(5,323)	(83.94)	(0.00610)
Amount purchase $(£1000)^4$		0.00702***	0.00601***	-476,604	39,921**	63.77	0.000688
		(0.000293)	(0.000292)	(1.272×10^{6})	(19,332)	(79.75)	(0.000511)
Amount purchase $(£1000)^5$		-0.000203***	-0.000173***	2.934×10^{6}	-55,165**	-21.32	-1.85×10^{-5}
		(9.72×10^{-6})	(9.66×10^{-6})	(7.782×10^{6})	(27,082)	(29.21)	(1.50×10^{-5})
Median house price (£)	1.79×10^{-7}***	1.13×10^{-7}***	1.02×10^{-7}***	-7.25×10^{-8}	1.17×10^{-7}	1.36×10^{-7}**	1.22×10^{-7}*
	(4.00×10^{-8})	(3.56×10^{-8})	(3.51×10^{-8})	(7.40×10^{-8})	(7.45×10^{-8})	(6.05×10^{-8})	(6.62×10^{-8})
Free school meals (proportion)	-0.248***	-0.341***	-0.306***	-0.343***	-0.272***	-0.219***	-0.463***
	(0.0445)	(0.0397)	(0.0393)	(0.0784)	(0.0789)	(0.0722)	(0.0737)
Weekly Household Income (£)	-3.33×10^{-5}	4.60×10^{-5}*	4.59×10^{-5}*	-6.51×10^{-5}	9.43×10^{-6}	0.000128***	4.83×10^{-5}
	(3.06×10^{-5})	(2.73×10^{-5})	(2.69×10^{-5})	(5.60×10^{-5})	(5.62×10^{-5})	(4.80×10^{-5})	(4.95×10^{-5})
Constant	0.434***	0.730***	0.615***	0.870***	3.066***	1.351	0.348***
	(0.0215)	(0.0194)	(0.0227)	(0.125)	(1.074)	(0.947)	(0.0628)
Observations	38,481	38,481	38,481	5,895	10,116	13,560	8,910
R-squared	0.017	0.220	0.243	0.023	0.054	0.085	0.094
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.3.4 replicates Table B.3.3 specifications but including socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to one or more merchant code (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £59.93. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B.4 Omitting travel related categories

Table B.4.1 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable = 1	0.300***	0.102***	0.104***	0.0432***	0.135***	0.101***	0.0391***
	(0.00714)	(0.00668)	(0.00660)	(0.00899)	(0.0144)	(0.0184)	(0.0144)
Merchant APR (%)			0.00593***	0.00320***	0.00754***	0.00899***	0.00688***
			(0.000372)	(0.000487)	(0.000854)	(0.00101)	(0.000873)
Credit limit (£1000)			0.00218	-0.00140	0.00749**	0.00515	0.00159
			(0.00139)	(0.00202)	(0.00328)	(0.00422)	(0.00418)
Utilization (%)			-0.00156***	-0.00712***	-0.00182*	-0.00207***	-0.000516
			(0.000253)	(0.00231)	(0.00109)	(0.000512)	(0.000406)
Account age (years)			0.104***	-0.00428	0.169***	0.247***	0.274***
			(0.0135)	(0.0173)	(0.0321)	(0.0353)	(0.0305)
Amount purchase (£1000)		-1.047***	-0.926***	33.60**	24.52	-77.75**	-0.246***
		(0.0190)	(0.0229)	(13.64)	(66.68)	(33.07)	(0.0698)
Amount purchase $(£1000)^2$		0.465***	0.425***	-1,881**	-266.3	275.9**	0.0814***
		(0.0130)	(0.0133)	(872.1)	(814.0)	(121.6)	(0.0286)
Amount purchase $(£1000)^3$		-0.0828***	-0.0763***	45,239*	1,255	-473.8**	-0.0119**
		(0.00302)	(0.00303)	(24,462)	(4,775)	(216.1)	(0.00497)
Amount purchase $(£1000)^4$		0.00619***	0.00572***	-505,934	-2,701	393.8**	0.000788**
		(0.000274)	(0.000273)	(309,979)	(13,500)	(186.0)	(0.000373)
Amount purchase $(£1000)^5$		-0.000161***	-0.000149***	2.128×10^{6}	2,124	-127.1**	-1.90×10^{-5}*
		(8.24×10^{-6})	(8.19×10^{-6})	(1.450×10^{6})	(14,763)	(62.20)	(9.91×10^{-6})
Constant	0.421***	0.760***	0.686***	0.647***	-0.246	8.721**	0.268***
	(0.00476)	(0.00612)	(0.0176)	(0.0767)	(2.096)	(3.474)	(0.0629)
Observations	17,870	17,870	17,870	7,139	4,543	3,238	2,950
Observations Non-durable = 1	7,929	7,929	7,929	4,654	2,058	752	465
R-squared	0.090	0.321	0.338	0.033	0.081	0.091	0.094
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. The sample is restricted to new accounts and includes months in which purchases were related to only one merchant code. Months with travel related expenditures are omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.4.2 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable = 1	0.286***	0.0948***	0.0957***	0.0402***	0.132***	0.0816***	0.0452**
	(0.00853)	(0.00799)	(0.00791)	(0.0102)	(0.0173)	(0.0237)	(0.0196)
Merchant APR (%)			0.00531***	0.00281***	0.00732***	0.00875***	0.00632***
			(0.000418)	(0.000539)	(0.000960)	(0.00117)	(0.00104)
Credit limit (£1000)			0.00196	-0.000100	0.00517	0.00393	-0.00997*
			(0.00162)	(0.00231)	(0.00381)	(0.00513)	(0.00564)
Utilization (%)			-0.00194***	-0.00866***	-0.00231*	-0.00261***	-0.00160***
			(0.000315)	(0.00271)	(0.00128)	(0.000648)	(0.000568)
Account age (years)			0.0892***	-0.0154	0.160***	0.215***	0.247***
			(0.0159)	(0.0197)	(0.0380)	(0.0437)	(0.0386)
Amount purchase (£1000)		-1.065***	-0.933***	21.69	-0.114	-105.9**	-0.207**
		(0.0245)	(0.0292)	(15.27)	(80.61)	(42.27)	(0.104)
Amount purchase (£1000)^2		0.485***	0.443***	-1,229	36.83	387.6**	0.0699
		(0.0177)	(0.0181)	(983.1)	(984.2)	(155.8)	(0.0446)
Amount purchase (£1000)^3		-0.0899***	-0.0830***	30,516	-554.2	-685.0**	-0.00978
		(0.00435)	(0.00436)	(27,725)	(5,775)	(277.8)	(0.00812)
Amount purchase (£1000)^4		0.00707***	0.00654***	-357,990	2,496	585.0**	0.000625
		(0.000415)	(0.000414)	(352,725)	(16,332)	(239.9)	(0.000640)
Amount purchase (£1000)^5		-0.000195***	-0.000181***	1.586x10^{6}	-3,598	-193.7**	-1.51x10^{-5}
		(1.32x10^{-5})	(1.31x10^{-5})	(1.655x10^{6})	(17,864)	(80.49)	(1.79x10^{-5})
Median house price (£)	8.43x10^{-8}	5.47x10^{-8}	5.23x10^{-8}	-1.01x10^{-7}	4.86x10^{-8}	2.09x10^{-7}	2.19x10^{-7}*
	(7.08x10^{-8})	(6.13x10^{-8})	(6.07x10^{-8})	(8.78x10^{-8})	(1.28x10^{-7})	(1.60x10^{-7})	(1.17x10^{-7})
Free school meals (proportion)	-0.197***	-0.239***	-0.216***	-0.226***	-0.0868	-0.310*	-0.269**
	(0.0748)	(0.0649)	(0.0644)	(0.0862)	(0.148)	(0.174)	(0.127)
Weekly Household Income (£)	-4.73x10^{-5}	-1.61x10^{-5}	-7.12x10^{-6}	-1.44x10^{-5}	7.81x10^{-5}	-3.42x10^{-5}	-7.73x10^{-5}
	(5.34x10^{-5})	(4.63x10^{-5})	(4.58x10^{-5})	(6.32x10^{-5})	(0.000102)	(0.000123)	(9.11x10^{-5})
Constant	0.504***	0.816***	0.761***	0.776***	0.569	11.51***	0.407***
	(0.0365)	(0.0320)	(0.0375)	(0.0949)	(2.535)	(4.432)	(0.111)
Observations	12,341	12,341	12,341	5,259	3,117	2,136	1,829
Observations Non-durable = 1	5,519	5,519	5,519	3,399	1,361	474	285
R-squared	0.085	0.313	0.329	0.030	0.085	0.094	0.096
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.4.2 replicates Table B.4.1 specifications with the addition of socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to only one spending type. Months with travel related expenditures are omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.4.3 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable (proportion)	0.316***	0.148***	0.152***	0.0439***	0.166***	0.226***	0.137***
	(0.00548)	(0.00528)	(0.00521)	(0.00841)	(0.0103)	(0.0107)	(0.0113)
Merchant APR (%)			0.00621***	0.00380***	0.00670***	0.00673***	0.00598***
			(0.000280)	(0.000430)	(0.000536)	(0.000613)	(0.000748)
Credit limit (£1000)			0.00626***	0.000948	0.0106***	0.0105***	0.00354
			(0.00103)	(0.00181)	(0.00211)	(0.00219)	(0.00286)
Utilization (%)			-0.00183***	-0.00546***	-0.00144**	-0.00184***	-0.00106***
			(0.000166)	(0.00185)	(0.000604)	(0.000286)	(0.000295)
Account age (years)			0.134***	0.00524	0.156***	0.235***	0.238***
			(0.0110)	(0.0156)	(0.0220)	(0.0249)	(0.0272)
Amount purchase (£1000)		-0.913***	-0.760***	27.93**	52.05	11.94	-0.165***
		(0.0130)	(0.0156)	(12.62)	(41.95)	(17.19)	(0.0562)
Amount purchase (£1000)^2		0.421***	0.361***	-1,508*	-633.7	-40.91	0.0477*
		(0.00948)	(0.00975)	(790.8)	(507.4)	(63.00)	(0.0244)
Amount purchase (£1000)^3		-0.0785***	-0.0678***	34,622	3,634	64.99	-0.00649
		(0.00235)	(0.00236)	(21,793)	(2,952)	(111.6)	(0.00444)
Amount purchase (£1000)^4		0.00613***	0.00530***	-371,200	-10,047	-49.43	0.000423
		(0.000223)	(0.000223)	(271,889)	(8,281)	(95.80)	(0.000346)
Amount purchase (£1000)^5		-0.000165***	-0.000143***	1.503×10^{6}	10,760	14.62	-1.04×10^{-5}
		(6.97×10^{-6})	(6.94×10^{-6})	(1.254×10^{6})	(8,993)	(31.94)	(9.49×10^{-6})
Constant	0.337***	0.693***	0.584***	0.661***	-1.151	-1.034	0.224***
	(0.00349)	(0.00494)	(0.0122)	(0.0719)	(1.331)	(1.812)	(0.0476)
Observations	42,857	42,857	42,857	9,639	12,350	12,950	7,918
R-squared	0.072	0.238	0.260	0.034	0.065	0.085	0.076
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.4.3 replicates Table B.4.1 specifications for the months with both consumption types. Months with travel related expenditures are omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.4.4 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £81.41)	OLS – Quartile 2 (Q2: £81.42 - £290.64)	OLS – Quartile 3 (Q3: £290.65 - £931.25)	OLS – Quartile 4 (£931.26 - £17000)
Non-durable (proportion)	0.301***	0.130***	0.134***	0.0389***	0.151***	0.201***	0.132***
	(0.00669)	(0.00639)	(0.00632)	(0.00956)	(0.0124)	(0.0138)	(0.0146)
Merchant APR (%)			0.00549***	0.00348***	0.00589***	0.00625***	0.00579***
			(0.000312)	(0.000476)	(0.000598)	(0.000691)	(0.000831)
Credit limit (£1000)			0.00555***	0.00244	0.00963***	0.00911***	-6.78x10^{-5}
			(0.00123)	(0.00207)	(0.00251)	(0.00274)	(0.00368)
Utilization (%)			-0.00180***	-0.00551**	-0.000902	-0.00194***	-0.00124***
			(0.000209)	(0.00219)	(0.000744)	(0.000369)	(0.000388)
Account age (years)			0.129***	-0.00845	0.159***	0.260***	0.225***
			(0.0130)	(0.0178)	(0.0260)	(0.0301)	(0.0333)
Amount purchase (£1000)		-0.962***	-0.812***	18.13	56.79	0.675	-0.144*
		(0.0169)	(0.0201)	(14.12)	(50.27)	(22.18)	(0.0796)
Amount purchase (£1000)^2		0.455***	0.395***	-1,010	-693.3	3.218	0.0397
		(0.0129)	(0.0132)	(890.2)	(609.3)	(81.43)	(0.0357)
Amount purchase (£1000)^3		-0.0880***	-0.0770***	24,040	3,959	-17.02	-0.00517
		(0.00333)	(0.00335)	(24,651)	(3,550)	(144.5)	(0.00675)
Amount purchase (£1000)^4		0.00718***	0.00630***	-268,093	-10,854	23.24	0.000334
		(0.000331)	(0.000331)	(308,719)	(9,972)	(124.3)	(0.000550)
Amount purchase (£1000)^5		-0.000204***	-0.000179***	1.119x10^{6}	11,515	-10.11	-8.59x10^{-6}
		(1.08x10^{-5})	(1.08x10^{-5})	(1.429x10^{6})	(10,842)	(41.52)	(1.58x10^{-5})
Median house price (£)	2.12x10^{-7}***	1.60x10^{-7}***	1.44x10^{-7}***	-1.45x10^{-8}	2.73x10^{-7}***	1.11x10^{-7}	1.54x10^{-7}*
	(4.67x10^{-8})	(4.20x10^{-8})	(4.15x10^{-8})	(7.73x10^{-8})	(8.33x10^{-8})	(7.62x10^{-8})	(8.65x10^{-8})
Free school meals (proportion)	-0.148***	-0.265***	-0.237***	-0.229***	-0.235***	-0.179*	-0.357***
	(0.0509)	(0.0458)	(0.0454)	(0.0751)	(0.0908)	(0.0932)	(0.0922)
Weekly Household Income (£)	-3.63x10^{-5}	9.35x10^{-6}	1.29x10^{-5}	-5.87x10^{-5}	-2.83x10^{-5}	0.000125**	1.45x10^{-5}
	(3.53x10^{-5})	(3.18x10^{-5})	(3.14x10^{-5})	(5.54x10^{-5})	(6.41x10^{-5})	(6.07x10^{-5})	(6.32x10^{-5})
Constant	0.382***	0.727***	0.620***	0.791***	-1.257	0.0211	0.244***
	(0.0246)	(0.0226)	(0.0262)	(0.0875)	(1.592)	(2.334)	(0.0783)
Observations	28,260	28,260	28,260	7,120	8,386	7,989	4,765
R-squared	0.069	0.246	0.265	0.031	0.064	0.088	0.087
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.4.4 replicates Table B.4.3 specifications but including socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to one or more purchase types. Months with travel related expenditures are omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £81.41. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.4.5 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable = 1	0.0599***	0.0192***	0.0202***	0.0575***	0.0190***	0.0195***	0.0153***	0.00430*	0.00425*
	(0.00172)	(0.00174)	(0.00171)	(0.00206)	(0.00209)	(0.00205)	(0.00222)	(0.00226)	(0.00226)
Merchant APR (%)			0.00941***			0.00809***			0.00254***
			(0.000163)			(0.000199)			(0.000419)
Credit limit (£1000)			-0.00277***			-0.00255***			0.00544
			(0.000390)			(0.000456)			(0.00394)
Utilization (%)			-0.00349***			-0.00362***			-0.000975***
			(0.000108)			(0.000131)			(0.000185)
Account age (years)			0.00448***			0.00428***			-0.0123***
			(0.000141)			(0.000158)			(0.00185)
Amount purchase (£1000)		-0.385***	-0.228***		-0.369***	-0.218***		-0.152***	-0.116***
		(0.00628)	(0.00739)		(0.00744)	(0.00878)		(0.00887)	(0.0111)
Amount purchase $(£1000)^2$		0.117***	0.0880***		0.113***	0.0850***		0.0552***	0.0477***
		(0.00428)	(0.00426)		(0.00501)	(0.00502)		(0.00635)	(0.00652)
Amount purchase $(£1000)^3$		-0.0160***	-0.0131***		-0.0155***	-0.0126***		-0.00842***	-0.00757***
		(0.000936)	(0.000917)		(0.00108)	(0.00106)		(0.00143)	(0.00144)
Amount purchase $(£1000)^4$		0.000954***	0.000816***		0.000919***	0.000773***		0.000514***	0.000473***
		($7.68x10^{-5}$)	($7.49x10^{-5}$)		($8.69x10^{-5}$)	($8.53x10^{-5}$)		(0.000119)	(0.000119)
Amount purchase $(£1000)^5$		$-2.01x10^{-5}$***	$-1.77x10^{-5}$***		$-1.91x10^{-5}$***	$-1.64x10^{-5}$***		$-1.06x10^{-5}$***	$-9.96x10^{-6}$***
		($2.07x10^{-6}$)	($2.01x10^{-6}$)		($2.30x10^{-6}$)	($2.25x10^{-6}$)		($3.25x10^{-6}$)	($3.25x10^{-6}$)
Median house price (£)				$-3.47x10^{-9}$	$4.36x10^{-9}$	$-3.46x10^{-9}$			
				($2.33x10^{-8}$)	($2.20x10^{-8}$)	($2.11x10^{-8}$)			
Free school meals (proportion)				-0.246***	-0.229***	-0.157***			
				(0.0275)	(0.0259)	(0.0250)			
Weekly Household Income (£)				$-1.31x10^{-5}$	$-9.15x10^{-7}$	$1.10x10^{-5}$			
				($1.80x10^{-5}$)	($1.69x10^{-5}$)	($1.63x10^{-5}$)			
Constant	0.791***	0.884***	0.719***	0.839***	0.914***	0.750***			
	(0.00153)	(0.00180)	(0.00426)	(0.0126)	(0.0119)	(0.0124)			
R-squared							0.001	0.013	0.015
Observations	133,697	133,697	133,697	92,968	92,968	92,968	77,705	77,705	77,705
Number of accounts	85,153	85,153	85,153	59,014	59,014	59,014	29,161	29,161	29,161
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. The sample includes all accounts and includes months in which expenses were related to only one merchant code. Months with travel related expenditures are omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.4.6 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable (proportion)	0.0644***	0.0194***	0.0269***	0.0606***	0.0184***	0.0245***	0.0212***	0.00651***	0.00660***
	(0.00152)	(0.00154)	(0.00149)	(0.00181)	(0.00183)	(0.00179)	(0.00181)	(0.00184)	(0.00184)
Merchant APR (%)			0.0117***			0.0104***			0.00409***
			(0.000126)			(0.000153)			(0.000287)
Credit limit (£1000)			-0.00200***			-0.00206***			0.0109***
			(0.000352)			(0.000411)			(0.00273)
Utilization (%)			-0.00349***			-0.00361***			-0.00111***
			(7.90×10^{-5})			(9.68×10^{-5})			(0.000129)
Account age (years)			0.00600***			0.00575***			-0.00886***
			(0.000129)			(0.000145)			(0.00145)
Amount purchase (£1000)		-0.400***	-0.203***		-0.377***	-0.197***		-0.171***	-0.131***
		(0.00475)	(0.00551)		(0.00566)	(0.00661)		(0.00626)	(0.00776)
Amount purchase $(£1000)^2$		0.134***	0.0836***		0.123***	0.0794***		0.0675***	0.0584***
		(0.00343)	(0.00338)		(0.00403)	(0.00400)		(0.00472)	(0.00482)
Amount purchase $(£1000)^3$		-0.0197***	-0.0131***		-0.0178***	-0.0122***		-0.0110***	-0.00987***
		(0.000790)	(0.000766)		(0.000909)	(0.000887)		(0.00112)	(0.00112)
Amount purchase $(£1000)^4$		0.00125***	0.000853***		0.00110***	0.000774***		0.000717***	0.000652***
		(6.77×10^{-5})	(6.52×10^{-5})		(7.61×10^{-5})	(7.40×10^{-5})		(9.75×10^{-5})	(9.77×10^{-5})
Amount purchase $(£1000)^5$		-2.79×10^{-5}***	-1.93×10^{-5}***		-2.40×10^{-5}***	-1.70×10^{-5}***		-1.58×10^{-5}***	-1.45×10^{-5}***
		(1.88×10^{-6})	(1.81×10^{-6})		(2.07×10^{-6})	(2.01×10^{-6})		(2.78×10^{-6})	(2.78×10^{-6})
Median house price (£)				7.05×10^{-8}***	6.78×10^{-8}***	4.23×10^{-8}***			
				(2.10×10^{-8})	(1.96×10^{-8})	(1.85×10^{-8})			
Free school meals (proportion)				-0.299***	-0.295***	-0.189***			
				(0.0245)	(0.0230)	(0.0217)			
Weekly household income (£)				-2.03×10^{-5}	2.44×10^{-6}	2.18×10^{-5}			
				(1.61×10^{-5})	(1.51×10^{-5})	(1.42×10^{-5})			
Constant	0.723***	0.845***	0.642***	0.776***	0.873***	0.661***			
	(0.00136)	(0.00165)	(0.00346)	(0.0113)	(0.0106)	(0.0107)			
R-squared							0.002	0.017	0.021
Observations	224,287	224,287	224,287	154,243	154,243	154,243	139,386	139,386	139,386
Number of accounts	133,310	133,310	133,310	90,823	90,823	90,823	48,409	48,409	48,409
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. Table B.4.6 replicates Table B.4.5 specifications but months with multiple consumption categories or merchant codes are added to the sample. However, months with travel related expenditures remain omitted from the sample (Hotel/Motel, Travel Agencies, Airlines, Other Transportation). All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B.5 Estimating Marginal Effects for Individual Merchant Codes

Table B.5.1 Estimated Likelihood of Repaying Full Balance for Single-Purchase-Type Sample, Durable Goods as Reference Category

	First purchase of new accounts		All accounts		
	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	OLS (+ socioeconomic controls)	RE	RE (+ socioeconomic controls)	FE
Non-durable merchant codes					
Airlines	0.0505***	0.0477**	0.0328***	0.0268***	0.0252***
	(0.0170)	(0.0213)	(0.00542)	(0.00673)	(0.00724)
Auto Rental	0.120***	0.147***	0.00178	0.00208	-0.0265***
	(0.0255)	(0.0302)	(0.00747)	(0.00893)	(0.00991)
Hotel/Motel	0.161***	0.147***	0.0522***	0.0544***	0.0131***
	(0.0152)	(0.0184)	(0.00379)	(0.00466)	(0.00468)
Restaurants/Bars	0.139***	0.140***	0.0406***	0.0408***	0.0112*
	(0.0168)	(0.0193)	(0.00454)	(0.00534)	(0.00580)
Travel Agencies	0.0243**	0.0296**	0.00993***	0.00121	0.0123**
	(0.0106)	(0.0133)	(0.00383)	(0.00467)	(0.00514)
Other Transportation	0.148***	0.134***	0.0463***	0.0429***	0.0169***
	(0.0175)	(0.0202)	(0.00490)	(0.00578)	(0.00630)
Drug Stores	0.139***	0.0949**	0.0349***	0.0270**	0.0141
	(0.0364)	(0.0410)	(0.00968)	(0.0115)	(0.0121)
Gas Stations	0.195***	0.184***	0.0554***	0.0516***	0.0107*
	(0.0122)	(0.0146)	(0.00398)	(0.00483)	(0.00565)
Mail Orders	0.0347*	0.0516**	-0.00259	-0.00292	-0.00444
	(0.0192)	(0.0237)	(0.00300)	(0.00362)	(0.00390)
Food Stores	0.146***	0.122***	0.0375***	0.0345***	0.00659*
	(0.00955)	(0.0116)	(0.00287)	(0.00356)	(0.00388)
Other Retail	0.0537***	0.0501***	0.0175***	0.0182***	0.00728**
	(0.0102)	(0.0123)	(0.00253)	(0.00306)	(0.00319)
Recreation	0.0451***	0.0391**	0.00965**	0.00993**	0.00304
	(0.0151)	(0.0181)	(0.00402)	(0.00484)	(0.00507)
Merchant APR (%)	0.00628***	0.00554***	0.0104***	0.00884***	0.00282***
	(0.000341)	(0.000385)	(0.000153)	(0.000187)	(0.000372)
Credit limit (£1000)	0.00262**	0.00170	-0.00274***	-0.00247***	0.00638*
	(0.00128)	(0.00151)	(0.000379)	(0.000443)	(0.00357)
Utilization (%)	-0.00148***	-0.00188***	-0.00320***	-0.00332***	-0.000724***
	(0.000216)	(0.000271)	(9.49×10^{-05})	(0.000115)	(0.000156)
Account age (years)	0.136***	0.124***	0.00495***	0.00470***	-0.0111***
	(0.0123)	(0.0146)	(0.000138)	(0.000155)	(0.00171)
Amount purchase (£1000)	-0.856***	-0.865***	-0.208***	-0.203***	-0.124***
	(0.0205)	(0.0263)	(0.00661)	(0.00790)	(0.00948)
Amount purchase (£1000)^2	0.392***	0.409***	0.0808***	0.0776***	0.0517***
	(0.0120)	(0.0164)	(0.00384)	(0.00454)	(0.00559)
Amount purchase (£1000)^3	-0.0710***	-0.0773***	-0.0122***	-0.0113***	-0.00836***
	(0.00277)	(0.00399)	(0.000840)	(0.000977)	(0.00126)
Amount purchase (£1000)^4	0.00538***	0.00616***	0.000772***	0.000690***	0.000537***
	(0.000252)	(0.000383)	(7.00×10^{-05})	(7.98×10^{-05})	(0.000107)
Amount purchase (£1000)^5	-0.000142***	-0.000172***	-1.71×10^{-05}***	-1.47×10^{-05}***	-1.17×10^{-05}***
	(7.65×10^{-06})	(1.22×10^{-05})	(1.90×10^{-06})	(2.14×10^{-06})	(2.99×10^{-06})
Median house price (£)		3.27×10^{-08}		-1.09×10^{-09}	
		(5.44×10^{-08})		(2.05×10^{-08})	
Free school meals (proportion)		-0.254***		-0.190***	
		(0.0585)		(0.0240)	
Weekly Household Income (£)		-1.17×10^{-05}		6.30×10^{-06}	
		(4.14×10^{-05})		(1.58×10^{-05})	
Constant	0.658***	0.744***	0.690***	0.734***	
	(0.0160)	(0.0340)	(0.00404)	(0.0119)	
R-squared	0.351	0.341			0.017
Observations	21,671	14,851	154,924	107,384	93,957
Number of accounts	21,671	14,851	95,461	66,021	34,494
Month FEs	YES	YES	YES	YES	YES

Note. Samples in all models include months in which expenses were related to only one merchant code. Models 1 and 2 evaluate the probability of full repayment of the first purchase made by new accounts. Models 3 to 5 include all accounts in the analysis. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Reference category: durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.5.2 Estimated Likelihood of Repaying Full Balance for Multiple-Purchase-Type Sample, Proportion of the Total Month Spending on Durable Goods as Reference Category

	First purchase of new accounts		All accounts		
	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	OLS (+ socioeconomic controls)	RE	RE (+ socioeconomic controls)	FE
Non-durable merchant codes (proportion)					
Airlines	0.0438***	0.0424**	0.0321***	0.0277***	0.0233***
	(0.0132)	(0.0167)	(0.00440)	(0.00545)	(0.00535)
Auto Rental	0.203***	0.211***	0.0283***	0.0271***	-0.00817
	(0.0218)	(0.0259)	(0.00641)	(0.00759)	(0.00757)
Hotel/Motel	0.257***	0.260***	0.0672***	0.0695***	0.0203***
	(0.0115)	(0.0140)	(0.00309)	(0.00376)	(0.00354)
Restaurants/Bars	0.265***	0.256***	0.0619***	0.0579***	0.0159***
	(0.0122)	(0.0141)	(0.00362)	(0.00423)	(0.00423)
Travel Agencies	0.00617	0.0145	0.0146***	0.00943**	0.0141***
	(0.00861)	(0.0109)	(0.00322)	(0.00393)	(0.00398)
Other Transportation	0.203***	0.189***	0.0550***	0.0524***	0.0156***
	(0.0141)	(0.0164)	(0.00417)	(0.00490)	(0.00492)
Drug Stores	0.143***	0.120***	0.0295***	0.0320***	0.0140
	(0.0284)	(0.0326)	(0.00802)	(0.00942)	(0.00918)
Gas Stations	0.260***	0.224***	0.0678***	0.0568***	0.0174***
	(0.00976)	(0.0119)	(0.00341)	(0.00412)	(0.00434)
Mail Orders	0.0347**	0.0452**	0.00534*	0.00330	-0.00264
	(0.0157)	(0.0194)	(0.00275)	(0.00330)	(0.00328)
Food Stores	0.199***	0.164***	0.0447***	0.0384***	0.0129***
	(0.00728)	(0.00898)	(0.00245)	(0.00302)	(0.00305)
Other Retail	0.0985***	0.104***	0.0246***	0.0259***	0.0111***
	(0.00840)	(0.0102)	(0.00222)	(0.00266)	(0.00257)
Recreation	0.109***	0.112***	0.0234***	0.0224***	0.00797**
	(0.0124)	(0.0150)	(0.00346)	(0.00416)	(0.00402)
Merchant APR (%)	0.00723***	0.00630***	0.0127***	0.0112***	0.00475***
	(0.000248)	(0.000277)	(0.000113)	(0.000137)	(0.000235)
Credit limit (£1000)	0.00713***	0.00561***	-0.00218***	-0.00235***	0.00958***
	(0.000908)	(0.00109)	(0.000334)	(0.000391)	(0.00236)
Utilization (%)	-0.00188***	-0.00192***	-0.00320***	-0.00326***	-0.000855***
	(0.000139)	(0.000174)	($6.68x10^{-05}$)	($8.17x10^{-05}$)	(0.000103)
Account age (years)	0.160***	0.157***	0.00672***	0.00640***	-0.00741***
	(0.00972)	(0.0115)	(0.000125)	(0.000141)	(0.00128)
Amount purchase (£1000)	-0.658***	-0.700***	-0.166***	-0.161***	-0.125***
	(0.0133)	(0.0170)	(0.00468)	(0.00561)	(0.00623)
Amount purchase (£1000)^2	0.316***	0.343***	0.0717***	0.0665***	0.0571***
	(0.00838)	(0.0113)	(0.00289)	(0.00341)	(0.00391)
Amount purchase (£1000)^3	-0.0608***	-0.0681***	-0.0118***	-0.0105***	-0.0102***
	(0.00207)	(0.00290)	(0.000672)	(0.000775)	(0.000937)
Amount purchase (£1000)^4	0.00486***	0.00569***	0.000815***	0.000692***	0.000720***
	(0.000199)	(0.000290)	($5.88x10^{-05}$)	($6.65x10^{-05}$)	($8.47x10^{-05}$)
Amount purchase (£1000)^5	-0.000134***	-0.000164***	$-1.93x10^{-05}$***	$-1.58x10^{-05}$***	$-1.72x10^{-05}$***
	($6.27x10^{-06}$)	($9.59x10^{-06}$)	($1.66x10^{-06}$)	($1.85x10^{-06}$)	($2.48x10^{-06}$)
Median house price (£)		$1.07x10^{-07}$***		$5.04x10^{-08}$***	
		($3.48x10^{-08}$)		($1.71x10^{-08}$)	
Free school meals (proportion)		-0.276***		-0.224***	
		(0.0389)		(0.0202)	
Weekly Household Income (£)		$2.97x10^{-05}$		$1.23x10^{-05}$	
		($2.67x10^{-05}$)		($1.32x10^{-05}$)	
Constant	0.541***	0.580***	0.603***	0.635***	
	(0.0107)	(0.0225)	(0.00319)	(0.00997)	
R-squared	0.257	0.259			0.022
Observations	58,404	38,481	282,997	194,214	184,673
Number of accounts	58,404	38,481	159,100	108,050	60,776
Month FEs	YES	YES	YES	YES	YES

Note. Table B.5.2 replicates Table B.5.1 specifications but months with multiple consumption categories or merchant codes are added to the sample. Models 1 and 2 evaluate the probability of full repayment of the first purchase made by new accounts. Models 3 to 5 include all accounts in the analysis. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.5.3 Estimated Likelihood of Repaying Full Balance for Single-Purchase-Type Sample, Non-Durable Goods as Reference Category

	First purchase of new accounts		All accounts		
	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	OLS (+ socioeconomic controls)	RE	RE (+ socioeconomic controls)	FE
Durable merchant codes					
Department Stores	-0.0436**	-0.0316	-0.0229***	-0.0186***	-0.0145**
	(0.0188)	(0.0221)	(0.00478)	(0.00569)	(0.00578)
Discount Stores	-0.162***	-0.161***	-0.0224***	-0.0205**	-0.00168
	(0.0239)	(0.0283)	(0.00683)	(0.00823)	(0.00823)
Clothing Stores	-0.0910***	-0.0884***	-0.0346***	-0.0345***	-0.0129***
	(0.0114)	(0.0134)	(0.00326)	(0.00396)	(0.00412)
Hardware Stores	-0.0876***	-0.0952***	-0.0114***	-0.0111**	0.00150
	(0.0159)	(0.0197)	(0.00415)	(0.00496)	(0.00510)
Vehicles	-0.109***	-0.103***	-0.0397***	-0.0375***	-0.00700
	(0.0129)	(0.0160)	(0.00398)	(0.00477)	(0.00502)
Interior Furnishing Stores	-0.0948***	-0.0900***	0.00391	0.00647	-0.00143
	(0.0151)	(0.0186)	(0.00441)	(0.00532)	(0.00545)
Electric Appliance Stores	-0.124***	-0.108***	-0.0289***	-0.0289***	-0.00729
	(0.0133)	(0.0160)	(0.00379)	(0.00452)	(0.00468)
Sporting Goods/Toy Stores	-0.134***	-0.126***	-0.0328***	-0.0285***	0.00438
	(0.0183)	(0.0224)	(0.00554)	(0.00672)	(0.00710)
Health Care	-0.111***	-0.104***	-0.0188***	-0.0155**	-0.00355
	(0.0203)	(0.0251)	(0.00513)	(0.00610)	(0.00616)
Education	-0.0382	-0.0353	-0.0355***	-0.0279**	0.00534
	(0.0296)	(0.0356)	(0.0111)	(0.0131)	(0.0149)
Professional Services	-0.127***	-0.134***	-0.0309***	-0.0308***	-0.0116***
	(0.0122)	(0.0148)	(0.00287)	(0.00344)	(0.00365)
Repair Shops	-0.147	-0.177	-0.00291	0.000571	0.0258
	(0.101)	(0.122)	(0.0251)	(0.0280)	(0.0295)
Other Services	-0.0473***	-0.0425***	-0.0187***	-0.0148***	-0.00678*
	(0.0107)	(0.0127)	(0.00296)	(0.00353)	(0.00381)
Merchant APR (%)	0.00620***	0.00553***	0.0103***	0.00875***	0.00280***
	(0.000343)	(0.000386)	(0.000153)	(0.000187)	(0.000372)
Credit limit (£1000)	0.00235*	0.00149	-0.00284***	-0.00254***	0.00640*
	(0.00129)	(0.00151)	(0.000379)	(0.000444)	(0.00357)
Utilization (%)	-0.00151***	-0.00190***	-0.00322***	-0.00333***	-0.000731***
	(0.000217)	(0.000272)	($9.50\text{x}10^{-05}$)	(0.000115)	(0.000156)
Account age (years)	0.126***	0.115***	0.00483***	0.00460***	-0.0112***
	(0.0123)	(0.0146)	(0.000138)	(0.000155)	(0.00171)
Amount purchase (£1000)	-0.911***	-0.907***	-0.213***	-0.209***	-0.120***
	(0.0200)	(0.0256)	(0.00645)	(0.00773)	(0.00934)
Amount purchase $(£1000)^2$	0.414***	0.426***	0.0821***	0.0793***	0.0502***
	(0.0119)	(0.0162)	(0.00380)	(0.00450)	(0.00556)
Amount purchase $(£1000)^3$	-0.0746***	-0.0800***	-0.0123***	-0.0114***	-0.00813***
	(0.00276)	(0.00398)	(0.000837)	(0.000974)	(0.00126)
Amount purchase $(£1000)^4$	0.00563***	0.00635***	0.000771***	0.000689***	0.000523***
	(0.000252)	(0.000382)	($6.99\text{x}10^{-05}$)	($7.97\text{x}10^{-05}$)	(0.000107)
Amount purchase $(£1000)^5$	-0.000148***	-0.000176***	$-1.69\text{x}10^{-05}$***	$-1.45\text{x}10^{-05}$***	$-1.14\text{x}10^{-05}$***
	($7.66\text{x}10^{-06}$)	($1.22\text{x}10^{-05}$)	($1.90\text{x}10^{-06}$)	($2.14\text{x}10^{-06}$)	($2.99\text{x}10^{-06}$)
Median house price (£)		$2.08\text{x}10^{-08}$		$-1.39\text{x}10^{-09}$	
		($5.45\text{x}10^{-08}$)		($2.05\text{x}10^{-08}$)	
Free school meals (proportion)		-0.279***		-0.193***	
		(0.0587)		(0.0240)	
Weekly Household Income (£)		$-1.44\text{x}10^{-05}$		$5.88\text{x}10^{-06}$	
		($4.15\ \text{x}10^{-05}$)		($1.58\ \text{x}10^{-05}$)	
Constant	0.776***	0.857***	0.719***	0.761***	
	(0.0157)	(0.0340)	(0.00395)	(0.0119)	
R-squared	0.346	0.337			0.016
Observations	21,671	14,851	154,924	107,384	93,957
Number of accounts	21,671	14,851	95,461	66,021	34,494
Month FEs	YES	YES	YES	YES	YES

Note. Samples in all models include months in which expenses were related to only one merchant code. Models 1 and 2 evaluate the probability of full repayment of the first purchase made by new accounts. Models 3 to 5 include all accounts in the analysis. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Reference category: non-durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.5.4 Estimated Likelihood of Repaying Full Balance for Multiple-Purchase-Type Sample, Proportion of the Total Month Spending on Non-Durable Goods as Reference Category

	First purchase of new accounts		All accounts		
	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	OLS (+ socioeconomic controls)	RE	RE (+ socioeconomic controls)	FE
Durable merchant codes (proportion)					
Department Stores	-0.103***	-0.0950***	-0.0330***	-0.0288***	-0.0191***
	(0.0145)	(0.0176)	(0.00401)	(0.00479)	(0.00458)
Discount Stores	-0.246***	-0.218***	-0.0492***	-0.0440***	-0.00676
	(0.0190)	(0.0227)	(0.00588)	(0.00704)	(0.00676)
Clothing Stores	-0.146***	-0.137***	-0.0523***	-0.0487***	-0.0212***
	(0.00889)	(0.0107)	(0.00275)	(0.00331)	(0.00323)
Hardware Stores	-0.136***	-0.146***	-0.0280***	-0.0272***	-0.00754*
	(0.0124)	(0.0154)	(0.00356)	(0.00425)	(0.00412)
Vehicles	-0.163***	-0.163***	-0.0447***	-0.0440***	-0.0104***
	(0.0103)	(0.0129)	(0.00336)	(0.00404)	(0.00400)
Interior Furnishing Stores	-0.170***	-0.171***	-0.0214***	-0.0172***	-0.00627
	(0.0114)	(0.0143)	(0.00365)	(0.00441)	(0.00427)
Electric Appliance Stores	-0.169***	-0.148***	-0.0363***	-0.0344***	-0.0117***
	(0.0107)	(0.0130)	(0.00325)	(0.00389)	(0.00379)
Sporting Goods/Toy Stores	-0.206***	-0.194***	-0.0480***	-0.0450***	-0.000204
	(0.0147)	(0.0180)	(0.00471)	(0.00567)	(0.00557)
Health Care	-0.149***	-0.138***	-0.0227***	-0.0198***	-0.00709
	(0.0169)	(0.0209)	(0.00442)	(0.00523)	(0.00503)
Education	-0.104***	-0.119***	-0.0456***	-0.0417***	-0.0184
	(0.0253)	(0.0305)	(0.00949)	(0.0112)	(0.0116)
Professional Services	-0.166***	-0.169***	-0.0312***	-0.0288***	-0.0112***
	(0.0101)	(0.0124)	(0.00256)	(0.00306)	(0.00303)
Repair Shops	-0.131*	-0.195**	-0.0181	-0.0150	0.00719
	(0.0766)	(0.0945)	(0.0216)	(0.0243)	(0.0245)
Other Services	-0.0926***	-0.0828***	-0.0293***	-0.0267***	-0.0106***
	(0.00880)	(0.0105)	(0.00258)	(0.00306)	(0.00305)
Merchant APR (%)	0.00702***	0.00618***	0.0125***	0.0111***	0.00474***
	(0.000249)	(0.000278)	(0.000113)	(0.000137)	(0.000235)
Credit limit (£1000)	0.00729***	0.00575***	-0.00225***	-0.00240***	0.00956***
	(0.000915)	(0.00109)	(0.000335)	(0.000392)	(0.00236)
Utilization (%)	-0.00200***	-0.00202***	-0.00323***	-0.00328***	-0.000863***
	(0.000140)	(0.000175)	(6.69x10^{-05})	(8.18x10^{-05})	(0.000104)
Account age (years)	0.142***	0.145***	0.00655***	0.00624***	-0.00747***
	(0.00976)	(0.0115)	(0.000125)	(0.000141)	(0.00128)
Amount purchase (£1000)	-0.692***	-0.720***	-0.168***	-0.162***	-0.123***
	(0.0133)	(0.0170)	(0.00461)	(0.00553)	(0.00617)
Amount purchase (£1000)^2	0.322***	0.344***	0.0708***	0.0654***	0.0565***
	(0.00842)	(0.0113)	(0.00288)	(0.00339)	(0.00389)
Amount purchase (£1000)^3	-0.0607***	-0.0674***	-0.0115***	-0.0101***	-0.0101***
	(0.00208)	(0.00291)	(0.000671)	(0.000774)	(0.000936)
Amount purchase (£1000)^4	0.00481***	0.00559***	0.000786***	0.000662***	0.000715***
	(0.000200)	(0.000291)	(5.87x10^{-05})	(6.64x10^{-05})	(8.46x10^{-05})
Amount purchase (£1000)^5	-0.000132***	-0.000161***	-1.85x10^{-05}***	-1.50x10^{-05}***	-1.71x10^{-05}***
	(6.31x10^{-06})	(9.63x10^{-06})	(1.66x10^{-06})	(1.85x10^{-06})	(2.48x10^{-06})
Median house price (£)		9.94x10^{-08}***		5.05x10^{-08}***	
		(3.49x10^{-08})		(1.71x10^{-08})	
Free school meals (proportion)		-0.301***		-0.227***	
		(0.0391)		(0.0202)	
Weekly Household Income (£)		3.59x10^{-05}		1.34x10^{-05}	
		(2.68x10^{-05})		(1.33x10^{-05})	
Constant	0.716***	0.737***	0.643***	0.671***	
	(0.0105)	(0.0225)	(0.00309)	(0.00995)	
R-squared	0.247	0.252			0.021
Observations	58,404	38,481	282,997	194,214	184,673
Number of accounts	58,404	38,481	159,100	108,050	60,776
Month FEs	YES	YES	YES	YES	YES

Note. Table B.5.4 replicates Table B.5.3 specifications but months with multiple consumption categories or merchant codes are added to the sample. Models 1 and 2 evaluate the probability of full repayment of the first purchase made by new accounts. Models 3 to 5 include all accounts in the analysis. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Reference category: Proportion of the total month spending on non-durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B.6 Regressions with Consumers Holding Multiple Cards

Table B.6.1 Estimated Likelihood of Repaying Full Balance, Cardholders Holding Multiple Cards in Main Samples

VARIABLES	(1) New Accounts - SP	(2) New Accounts - MP	(3) All Accounts - SP	(4) All Accounts - MP
Non-durable (proportion)		0.149***		0.0448***
		(0.0124)		(0.00390)
Non-durable = 1	0.0836***		0.0293***	
	(0.0163)		(0.00465)	
Merchant APR (%)	0.00589***	0.00799***	0.00940***	0.0120***
	(0.00117)	(0.000830)	(0.000446)	(0.000318)
Credit limit (£1000)	0.00318	0.00780***	-0.00140	-0.000173
	(0.00333)	(0.00229)	(0.000961)	(0.000841)
Utilization (%)	-0.000947	-0.00143***	-0.00437***	-0.00373***
	(0.000627)	(0.000400)	(0.000280)	(0.000194)
Account age (years)	0.0354	0.0644**	0.00467***	0.00620***
	(0.0384)	(0.0288)	(0.000390)	(0.000345)
Amount purchase (£1000)	-0.962***	-0.667***	-0.263***	-0.179***
	(0.0555)	(0.0352)	(0.0171)	(0.0118)
Amount purchase $(£1000)^2$	0.442***	0.304***	0.104***	0.0683***
	(0.0349)	(0.0230)	(0.00890)	(0.00658)
Amount purchase $(£1000)^3$	-0.0820***	-0.0578***	-0.0145***	-0.00957***
	(0.00844)	(0.00583)	(0.00174)	(0.00138)
Amount purchase $(£1000)^4$	0.00648***	0.00469***	0.000824***	0.000551***
	(0.000805)	(0.000577)	(0.000131)	(0.000110)
Amount purchase $(£1000)^5$	-0.000181***	-0.000134***	$-1.64\text{x}10^{-05}$***	$-1.10\text{x}10^{-05}$***
	$(2.57\text{x}10^{-05})$	$(1.90\text{x}10^{-05})$	$(3.31\text{x}10^{-06})$	$(2.87\text{x}10^{-06})$
Median house price (£)	$-7.29\text{x}10^{-08}$	$3.16\text{x}10^{-08}$	$1.18\text{x}10^{-07}$***	$8.44\text{x}10^{-08}$**
	$(1.28\text{x}10^{-07})$	$(8.33\text{x}10^{-08})$	$(4.51\text{x}10^{-08})$	$(3.70\text{x}10^{-08})$
Free school meals (proportion)	-0.0798	-0.373***	-0.101*	-0.246***
	(0.143)	(0.0909)	(0.0555)	(0.0456)
Weekly Household Income (£)	$9.47\text{x}10^{-05}$	$7.36\text{x}10^{-05}$	$-4.94\text{x}10^{-06}$	$1.30\text{x}10^{-05}$
	$(9.75\text{x}10^{-05})$	$(6.16\text{x}10^{-05})$	$(3.50\text{x}10^{-05})$	$(2.89\text{x}10^{-05})$
Constant	0.671***	0.524***	0.689***	0.598***
	(0.0829)	(0.0517)	(0.0271)	(0.0221)
Observations	2,613	7,644	20,255	38,390
R-squared	0.358	0.235		
Month FEs	YES	YES	YES	YES
Number of accounts			13,941	23,851

Note. The samples used on each column are subsets of each of the main samples used in Tables 3.4, 3.5, 3.6 and 3.7, Column 3. These subsets correspond to the account x months in which a cardholder hold multiple cards with positive balance and has postcode socioeconomic data. SP: Single Purchase Months; MP: Multiple Purchase Months. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.6.2 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Multiple Credit Card Cardholders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Non-durable = 1	0.0834***	0.0837***	0.0842***	0.0831***	0.0830***	0.0833***	0.0835***
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)
Merchant APR (%)	0.00583***	0.00586***	0.00596***	0.00583***	0.00583***	0.00587***	0.00585***
	(0.00117)	(0.00117)	(0.00117)	(0.00117)	(0.00117)	(0.00117)	(0.00117)
Credit limit (£1000)	0.00326	0.00322	0.00348	0.00411	0.00427	0.00335	0.00329
	(0.00333)	(0.00333)	(0.00332)	(0.00334)	(0.00334)	(0.00333)	(0.00333)
Utilization (%)	-0.000949	-0.000917	-0.000855	-0.00106*	-0.00101	-0.000917	-0.000924
	(0.000627)	(0.000627)	(0.000626)	(0.000628)	(0.000627)	(0.000627)	(0.000627)
Account age (years)	0.0359	0.0387	0.0375	0.0381	0.0390	0.0375	0.0383
	(0.0384)	(0.0385)	(0.0383)	(0.0384)	(0.0384)	(0.0384)	(0.0384)
Amount purchase (£1000)	-0.962***	-0.961***	-1.043***	-0.998***	-1.005***	-0.988***	-0.991***
	(0.0555)	(0.0554)	(0.0595)	(0.0570)	(0.0574)	(0.0577)	(0.0579)
Amount purchase (£1000)^2	0.442***	0.442***	0.476***	0.457***	0.460***	0.453***	0.454***
	(0.0349)	(0.0349)	(0.0360)	(0.0353)	(0.0354)	(0.0354)	(0.0355)
Amount purchase (£1000)^3	-0.0820***	-0.0819***	-0.0882***	-0.0848***	-0.0854***	-0.0839***	-0.0841***
	(0.00844)	(0.00843)	(0.00858)	(0.00849)	(0.00850)	(0.00851)	(0.00851)
Amount purchase (£1000)^4	0.00648***	0.00647***	0.00697***	0.00671***	0.00675***	0.00663***	0.00664***
	(0.000805)	(0.000805)	(0.000814)	(0.000808)	(0.000809)	(0.000810)	(0.000810)
Amount purchase (£1000)^5	-0.000181***	-0.000181***	-0.000195***	-0.000187***	-0.000189***	-0.000185***	-0.000185***
	(2.57x10^{-05})	(2.57x10^{-05})	(2.59x10^{-05})	(2.58x10^{-05})	(2.58x10^{-05})	(2.58x10^{-05})	(2.58x10^{-05})
Median house price (£)	-7.20x10^{-08}	-7.22x10^{-08}	-7.01x10^{-08}	-6.39x10^{-08}	-6.63x10^{-08}	-6.72x10^{-08}	-6.91x10^{-08}
	(1.28x10^{-07})	(1.28x10^{-07})	(1.28x10^{-07})	(1.28x10^{-07})	(1.28x10^{-07})	(1.28x10^{-07})	(1.28x10^{-07})
Free school meals (proportion)	-0.0761	-0.0773	-0.0675	-0.0629	-0.0655	-0.0747	-0.0752
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
Weekly Household Income (£)	9.54x10^{-05}	9.79x10^{-05}	0.000106	9.76x10^{-05}	9.76x10^{-05}	9.63x10^{-05}	9.73x10^{-05}
	(9.75x10^{-05})	(9.75x10^{-05})	(9.74x10^{-05})	(9.74x10^{-05})	(9.74x10^{-05})	(9.75x10^{-05})	(9.75x10^{-05})
Number of Cards w/ Positive Balance	0.000302	0.00207*	0.000397	0.000358	0.000172	0.000323	0.000225
	(0.000494)	(0.00120)	(0.000494)	(0.000494)	(0.000495)	(0.000494)	(0.000496)
Balance in other cards (£1000)		-0.00265					
		(0.00163)					
Ratio balance of card to total balance on all cards			0.121***				
			(0.0326)				
Card has the highest utilization = 1				0.0548***			
				(0.0200)			
Card has the lowest utilization = 1					-0.0567***		
					(0.0196)		
Card has the highest balance = 1						0.0331*	
						(0.0201)	
Card has the lowest balance =1							-0.0350*
							(0.0197)
Constant	0.669***	0.667***	0.633***	0.651***	0.708***	0.661***	0.696***
	(0.0829)	(0.0829)	(0.0833)	(0.0831)	(0.0839)	(0.0830)	(0.0843)
Observations	2,613	2,613	2,613	2,613	2,613	2,613	2,613
R-squared	0.358	0.359	0.361	0.360	0.360	0.359	0.359
Month FEs	YES	YES	YES	YES	YES	YES	YES

Note. The sample is based on the sample used in Table B.6.1, Column 1. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.6.3 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts, Multiple Credit Card Cardholders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Non-durable (proportion)	0.149***	0.151***	0.152***	0.149***	0.148***	0.150***	0.150***
	(0.0124)	(0.0124)	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0123)
Merchant APR (%)	0.00786***	0.00791***	0.00836***	0.00793***	0.00794***	0.00818***	0.00816***
	(0.000832)	(0.000830)	(0.000826)	(0.000825)	(0.000826)	(0.000829)	(0.000830)
Credit limit (£1000)	0.00789***	0.00773***	0.00836***	0.00972***	0.00978***	0.00830***	0.00824***
	(0.00229)	(0.00229)	(0.00228)	(0.00228)	(0.00229)	(0.00229)	(0.00229)
Utilization (%)	-0.00145***	-0.00142***	-0.00119***	-0.00155***	-0.00145***	-0.00129***	-0.00129***
	(0.000400)	(0.000399)	(0.000398)	(0.000397)	(0.000398)	(0.000399)	(0.000399)
Account age (years)	0.0654**	0.0722**	0.0667**	0.0664**	0.0658**	0.0672**	0.0668**
	(0.0288)	(0.0288)	(0.0286)	(0.0286)	(0.0286)	(0.0287)	(0.0287)
Amount purchase (£1000)	-0.665***	-0.662***	-0.792***	-0.743***	-0.743***	-0.732***	-0.734***
	(0.0352)	(0.0351)	(0.0367)	(0.0356)	(0.0358)	(0.0360)	(0.0362)
Amount purchase (£1000)^2	0.304***	0.303***	0.356***	0.336***	0.336***	0.329***	0.331***
	(0.0230)	(0.0230)	(0.0233)	(0.0230)	(0.0231)	(0.0231)	(0.0232)
Amount purchase (£1000)^3	-0.0577***	-0.0576***	-0.0676***	-0.0640***	-0.0640***	-0.0622***	-0.0628***
	(0.00582)	(0.00581)	(0.00584)	(0.00580)	(0.00582)	(0.00582)	(0.00584)
Amount purchase (£1000)^4	0.00469***	0.00468***	0.00549***	0.00521***	0.00521***	0.00503***	0.00509***
	(0.000577)	(0.000576)	(0.000577)	(0.000574)	(0.000575)	(0.000576)	(0.000577)
Amount purchase (£1000)^5	-0.000134***	-0.000134***	-0.000157***	-0.000149***	-0.000149***	-0.000144***	-0.000145***
	(1.90x10^{-05})	(1.90x10^{-05})	(1.90x10^{-05})	(1.89x10^{-05})	(1.90x10^{-05})	(1.90x10^{-05})	(1.90x10^{-05})
Median house price (£)	3.36x10^{-08}	2.93x10^{-08}	2.41x10^{-08}	2.67x10^{-08}	2.14x10^{-08}	2.66x10^{-08}	2.63x10^{-08}
	(8.33x10^{-08})	(8.31x10^{-08})	(8.26x10^{-08})	(8.26x10^{-08})	(8.27x10^{-08})	(8.29x10^{-08})	(8.30x10^{-08})
Free school meals (proportion)	-0.365***	-0.369***	-0.365***	-0.348***	-0.350***	-0.359***	-0.358***
	(0.0909)	(0.0908)	(0.0902)	(0.0902)	(0.0904)	(0.0906)	(0.0906)
Weekly Household Income (£)	7.50x10^{-05}	8.11x10^{-05}	9.43x10^{-05}	8.64x10^{-05}	8.96x10^{-05}	8.97x10^{-05}	8.85x10^{-05}
	(6.16x10^{-05})	(6.15x10^{-05})	(6.11x10^{-05})	(6.11x10^{-05})	(6.12x10^{-05})	(6.13x10^{-05})	(6.14x10^{-05})
Number of Cards w/ Positive Balance	0.000758**	0.00466***	0.000978***	0.000914***	0.000534	0.000836**	0.000569*
	(0.000344)	(0.000801)	(0.000342)	(0.000342)	(0.000343)	(0.000343)	(0.000344)
Balance in other cards (£1000)		-0.00638***					
		(0.00118)					
Ratio balance of card to total balance on all cards			0.209***				
			(0.0187)				
Card has the highest utilization = 1				0.124***			
				(0.0111)			
Card has the lowest utilization = 1					-0.110***		
					(0.0110)		
Card has the highest balance = 1						0.0915***	
						(0.0113)	
Card has the lowest balance =1							-0.0855***
							(0.0112)
Constant	0.519***	0.515***	0.456***	0.480***	0.589***	0.490***	0.577***
	(0.0518)	(0.0517)	(0.0517)	(0.0515)	(0.0519)	(0.0517)	(0.0521)
Observations	7,644	7,644	7,644	7,644	7,644	7,644	7,644
R-squared	0.235	0.238	0.247	0.248	0.245	0.242	0.241
Month FEs	YES	YES	YES	YES	YES	YES	YES

Note. The sample is based on the sample used in Table B.6.1, Column 2. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.6.4 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for All Accounts, Multiple Credit Card Cardholders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	RE	RE	RE	RE	RE	RE	RE
Non-durable = 1	0.0293***	0.0286***	0.0307***	0.0299***	0.0298***	0.0302***	0.0298***
	(0.00465)	(0.00464)	(0.00464)	(0.00464)	(0.00464)	(0.00465)	(0.00465)
Merchant APR (%)	0.00940***	0.00971***	0.00964***	0.00949***	0.00943***	0.00951***	0.00945***
	(0.000446)	(0.000446)	(0.000445)	(0.000444)	(0.000445)	(0.000445)	(0.000445)
Credit limit (£1000)	-0.00140	-0.000743	-0.000545	-0.000131	-0.000346	-0.00105	-0.00115
	(0.000961)	(0.000961)	(0.000961)	(0.000966)	(0.000969)	(0.000961)	(0.000962)
Utilization (%)	-0.00437***	-0.00423***	-0.00426***	-0.00460***	-0.00448***	-0.00432***	-0.00433***
	(0.000280)	(0.000280)	(0.000280)	(0.000280)	(0.000280)	(0.000280)	(0.000280)
Account age (years)	0.00467***	0.00443***	0.00433***	0.00445***	0.00451***	0.00454***	0.00458***
	(0.000390)	(0.000389)	(0.000389)	(0.000389)	(0.000389)	(0.000389)	(0.000390)
Amount purchase (£1000)	-0.263***	-0.264***	-0.339***	-0.302***	-0.295***	-0.296***	-0.288***
	(0.0171)	(0.0171)	(0.0186)	(0.0175)	(0.0176)	(0.0178)	(0.0178)
Amount purchase (£1000)^2	0.104***	0.104***	0.132***	0.119***	0.116***	0.115***	0.113***
	(0.00891)	(0.00889)	(0.00930)	(0.00902)	(0.00904)	(0.00907)	(0.00908)
Amount purchase (£1000)^3	-0.0145***	-0.0146***	-0.0186***	-0.0169***	-0.0162***	-0.0161***	-0.0157***
	(0.00174)	(0.00173)	(0.00178)	(0.00175)	(0.00175)	(0.00175)	(0.00176)
Amount purchase (£1000)^4	0.000824***	0.000832***	0.00108***	0.000976***	0.000933***	0.000925***	0.000902***
	(0.000131)	(0.000131)	(0.000133)	(0.000132)	(0.000132)	(0.000132)	(0.000132)
Amount purchase (£1000)^5	-1.64x10^{-05}***	-1.66x10^{-05}***	-2.19x10^{-05}***	-1.97x10^{-05}***	-1.87x10^{-05}***	-1.85x10^{-05}***	-1.80x10^{-05}***
	(3.31x10^{-06})	(3.30x10^{-06})	(3.34x10^{-06})	(3.32x10^{-06})	(3.32x10^{-06})	(3.32x10^{-06})	(3.32x10^{-06})
Median house price (£)	1.18x10^{-07}***	1.16x10^{-07}***	1.13x10^{-07}**	1.16x10^{-07}***	1.16x10^{-07}***	1.15x10^{-07}**	1.16x10^{-07}***
	(4.51x10^{-08})	(4.50x10^{-08})	(4.49x10^{-08})	(4.50x10^{-08})	(4.50x10^{-08})	(4.51x10^{-08})	(4.51x10^{-08})
Free school meals (proportion)	-0.101*	-0.100*	-0.0965*	-0.0941*	-0.0966*	-0.100*	-0.101*
	(0.0555)	(0.0553)	(0.0553)	(0.0553)	(0.0554)	(0.0554)	(0.0554)
Weekly Household Income (£)	-4.90x10^{-06}	2.20x10^{-06}	2.66x10^{-06}	-1.70x10^{-06}	-2.88x10^{-06}	-1.62x10^{-06}	-3.13x10^{-06}
	(3.50x10^{-05})	(3.49x10^{-05})	(3.49x10^{-05})	(3.49x10^{-05})	(3.49x10^{-05})	(3.50x10^{-05})	(3.50x10^{-05})
Number of Cards w/ Positive Balance	8.71x10^{-05}	0.00511***	0.000256	0.000191	-5.14x10^{-05}	0.000140	-7.30x10^{-06}
	(0.000434)	(0.000700)	(0.000432)	(0.000433)	(0.000433)	(0.000433)	(0.000434)
Balance in other cards (£1000)		-0.00733***					
		(0.000803)					
Ratio balance of card to total balance on all cards			0.106***				
			(0.0104)				
Card has the highest utilization = 1				0.0589***			
				(0.00595)			
Card has the lowest utilization = 1					-0.0416***		
					(0.00556)		
Card has the highest balance = 1						0.0409***	
						(0.00613)	
Card has the lowest balance =1							-0.0276***
							(0.00565)
Constant	0.689***	0.678***	0.662***	0.674***	0.719***	0.681***	0.712***
	(0.0272)	(0.0271)	(0.0272)	(0.0271)	(0.0274)	(0.0272)	(0.0275)
Observations	20,255	20,255	20,255	20,255	20,255	20,255	20,255
Number of accounts	13,941	13,941	13,941	13,941	13,941	13,941	13,941
Month FEs	YES	YES	YES	YES	YES	YES	YES

Note. The sample is based on the sample used in Table B.6.1, Column 3. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.6.5 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for All Accounts, Multiple Credit Card Cardholders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	RE	RE	RE	RE	RE	RE	RE
Non-durable (proportion)	0.0448***	0.0444***	0.0464***	0.0456***	0.0453***	0.0459***	0.0455***
	(0.00390)	(0.00389)	(0.00389)	(0.00389)	(0.00389)	(0.00389)	(0.00389)
Merchant APR (%)	0.0119***	0.0122***	0.0123***	0.0120***	0.0120***	0.0121***	0.0120***
	(0.000319)	(0.000318)	(0.000317)	(0.000317)	(0.000317)	(0.000318)	(0.000318)
Credit limit (£1000)	-0.000160	0.000636	0.000995	0.00160*	0.00139*	0.000391	0.000269
	(0.000841)	(0.000839)	(0.000836)	(0.000840)	(0.000843)	(0.000838)	(0.000839)
Utilization (%)	-0.00374***	-0.00360***	-0.00358***	-0.00394***	-0.00383***	-0.00366***	-0.00367***
	(0.000194)	(0.000194)	(0.000193)	(0.000194)	(0.000194)	(0.000194)	(0.000194)
Account age (years)	0.00621***	0.00591***	0.00568***	0.00585***	0.00594***	0.00596***	0.00603***
	(0.000345)	(0.000344)	(0.000343)	(0.000343)	(0.000344)	(0.000344)	(0.000344)
Amount purchase (£1000)	-0.179***	-0.179***	-0.280***	-0.236***	-0.228***	-0.229***	-0.220***
	(0.0118)	(0.0117)	(0.0128)	(0.0121)	(0.0122)	(0.0122)	(0.0123)
Amount purchase (£1000)^2	0.0683***	0.0683***	0.107***	0.0909***	0.0876***	0.0862***	0.0836***
	(0.00658)	(0.00656)	(0.00683)	(0.00666)	(0.00668)	(0.00668)	(0.00671)
Amount purchase (£1000)^3	-0.00957***	-0.00957***	-0.0156***	-0.0132***	-0.0126***	-0.0123***	-0.0119***
	(0.00138)	(0.00137)	(0.00140)	(0.00138)	(0.00139)	(0.00138)	(0.00139)
Amount purchase (£1000)^4	0.000551***	0.000556***	0.000937***	0.000790***	0.000747***	0.000721***	0.000704***
	(0.000110)	(0.000109)	(0.000111)	(0.000110)	(0.000110)	(0.000110)	(0.000110)
Amount purchase (£1000)^5	-1.10x10^{-05}***	-1.12x10^{-05}***	-1.96x10^{-05}***	-1.65x10^{-05}***	-1.54x10^{-05}***	-1.48x10^{-05}***	-1.45x10^{-05}***
	(2.87x10^{-06})	(2.86x10^{-06})	(2.89x10^{-06})	(2.87x10^{-06})	(2.87x10^{-06})	(2.87x10^{-06})	(2.88x10^{-06})
Median house price (£)	8.47x10^{-08}**	8.34x10^{-08}**	7.59x10^{-08}**	7.91x10^{-08}**	7.80x10^{-08}**	7.87x10^{-08}**	8.06x10^{-08}**
	(3.70x10^{-08})	(3.68x10^{-08})	(3.66x10^{-08})	(3.66x10^{-08})	(3.67x10^{-08})	(3.68x10^{-08})	(3.68x10^{-08})
Free school meals (proportion)	-0.244***	-0.244***	-0.242***	-0.235***	-0.238***	-0.243***	-0.243***
	(0.0456)	(0.0454)	(0.0452)	(0.0452)	(0.0454)	(0.0454)	(0.0455)
Weekly Household Income (£)	1.34x10^{-05}	2.05x10^{-05}	2.49x10^{-05}	1.88x10^{-05}	1.83x10^{-05}	2.04x10^{-05}	1.77x10^{-05}
	(2.89x10^{-05})	(2.87x10^{-05})	(2.86x10^{-05})	(2.86x10^{-05})	(2.87x10^{-05})	(2.87x10^{-05})	(2.88x10^{-05})
Number of Cards w/ Positive Balance	0.000510*	0.00651***	0.000760**	0.000668**	0.000347	0.000603**	0.000375
	(0.000300)	(0.000501)	(0.000298)	(0.000298)	(0.000299)	(0.000299)	(0.000300)
Balance in other cards (£1000)		-0.00934***					
		(0.000626)					
Ratio balance of card to total balance on all cards			0.147***				
			(0.00746)				
Card has the highest utilization = 1				0.0795***			
				(0.00417)			
Card has the lowest utilization = 1					-0.0600***		
					(0.00398)		
Card has the highest balance = 1						0.0617***	
						(0.00425)	
Card has the lowest balance =1							-0.0450***
							(0.00401)
Constant	0.596***	0.586***	0.558***	0.577***	0.639***	0.583***	0.632***
	(0.0221)	(0.0220)	(0.0220)	(0.0220)	(0.0222)	(0.0220)	(0.0223)
Observations	38,390	38,390	38,390	38,390	38,390	38,390	38,390
Number of accounts	23,851	23,851	23,851	23,851	23,851	23,851	23,851
Month FEs	YES	YES	YES	YES	YES	YES	YES

Note. The sample is based on the sample used in Table B.6.1, Column 4. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B.7 Reclassification of Categories Based on Survey Results

The classification of categories of expenditure as durable and non-durable in our main analysis follows the classification used in Kuchler (2013). One referee asked us to conduct a survey of consumers to generate an independent classification of expenditure types. We conducted a preregistered survey to estimate the durability of items from each merchant category, see https://aspredicted.org/f9iu4.pdf. The Argus data contains 27 main categories in total. We exclude 2 from our main analysis: cash and utilities. Many of the remaining 25 categories are very broad and might contain both durable and non-durable goods. Therefore, we obtained the next-level-down disaggregation of individual items and designed the survey based on these. Respondents were asked to rate the durability of each among 152 individual items on a 1-7 scale. We excluded from the survey items whose consumption is rare (with a weight of less than 1 in 1,000 in the 2014 UK Consumer Price Inflation indices (CPI)). The exact wording of the questions was as follows:

The survey sample was drawn from Prolific Academic, and restricted to UK Nationals living in the UK. The survey, which was conducted online, can be viewed here: http://www.stewart.warwick.ac.uk/expt/durability_1/ We collected responses from 501 participants. The survey received ethical approval from the University of Warwick Humanities and Social Sciences Research Ethics Committee, approval number 102/17-18. For each item, we constructed the mean durability score over participants. We then took the weighted average of durability scores within each category (using CPI weights). CPI weights reflect the levels of spending on different goods and services in the UK National Accounts and are used for the calculation of inflation statistics. Based on this approach we obtained a weighted mean durability score for each of the 25 spending categories. We have median split the 25 categories into low and high durability and repeat our main analysis using 25 reclassified categories. We have also use category non-durability scores (normalized between 0 and 1) in place of the 0/1 dummy for low/high non-durability and repeat the analysis (See Tables B.7.7 and B.7.8).

The detailed procedure to construct average weighted scores is defined as follows:

1. Data cleaning. As recorded in advance in our preregistration, we flagged: (1) participants who rate an airline ticket as more durable than a car, (2) the 5% fastest and 5% slowest participants, (3) participants with duplicated IP, (4) participants whose autocorrelation over successive

responses are in the top 2.5% of bottom 2.5% of the distribution, (5) participants whose responses scale entropy is in the lowest 5%, and (6) the 5% of participants with the lowest correlation between their ratings and the average of everyone else's ratings. Participants identified through this (non-sequential) procedure were dropped from the sample (112 participants from the 501 sample).

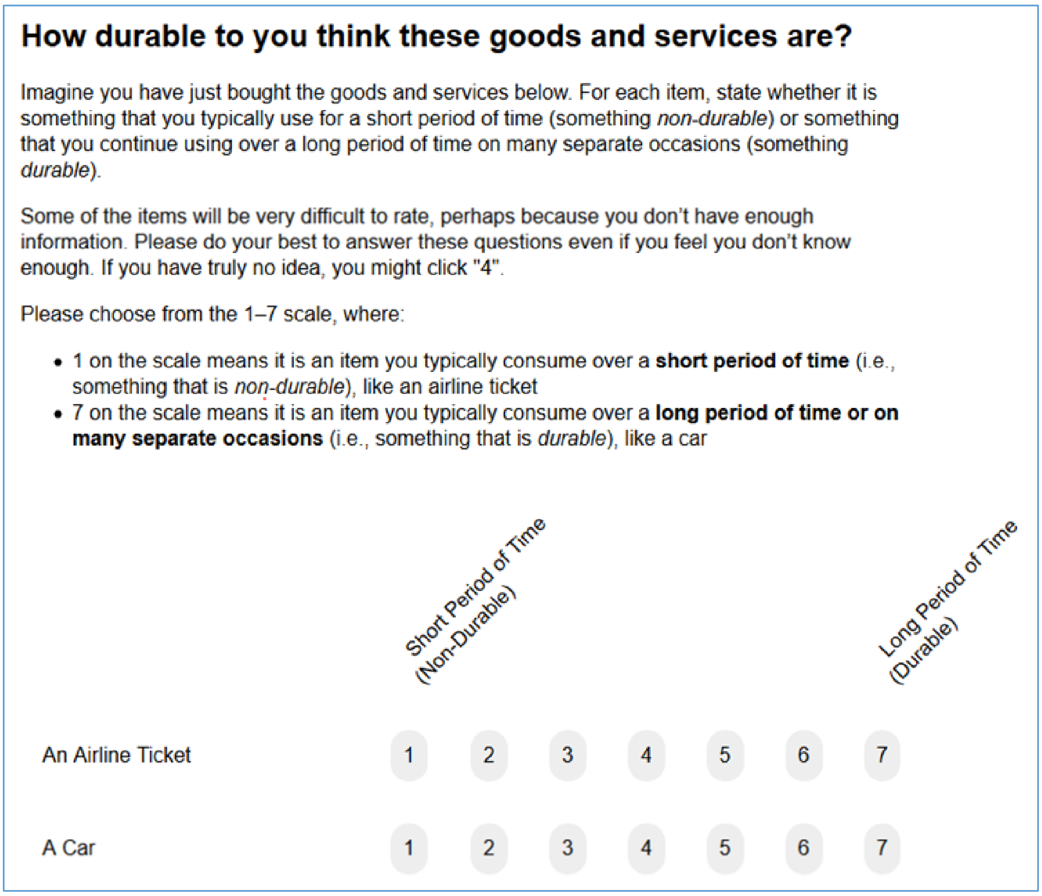
2. For each item, we computed the item mean score over participants.

3. We computed the relative weights for item within each merchant code. We have weights for each CPI subcategory, however, a subcategory can be matched to many items, e.g., the items 'An Item of Men's or Boy's Clothing', 'An Item of Women's Clothing', 'An Item of Children's Clothing', are related to the CPI subcategory '03.1 Clothing'. Or the items 'A Visit to the Osteopath', 'A Visit to the Chiropractor', 'A Visit to the Opticians', are related to the CPI subcategory '06.2.1/3 Medical services and paramedical services'. So, to prevent double counting or multiple counting weights, for each merchant code, we adjusted the item's weight to account for the number of items within CPI subcategories.

4. Then, for each merchant code, we computed a merchant code average durability, weighting the items durability (from step 2) with the relative weights (from step 3) and adding these weighted scores to get the merchant code score. The results from this procedure are displayed in Figure B.7.2A. The figure also shows merchant code scores that are just average of items scores (from step 2) and do not use any weight.

Tables B.7.1–B.7.6 use the durability classification of the merchant codes after median split the merchant codes from Figure B.7.2A into low and high durability. Tables B.7.7 and B.7.8 use the category non-durability scores (normalized between 0 and 1) in place of the 0/1 dummy for low/high non-durability and repeat the analysis. These scores are displayed in Figure B.7.2C).

While our data analysis procedure described is consistent with the preregistration of the study, to have an estimate of the uncertainty in the average scores obtained above, we also repeated the analysis but this time calculating scores within subjects. Thus, we omitted step 2 because each participant provided only one score for each item and we repeated steps 2 to 4 within participant. Figure B.7.2B shows the average merchant code scores along with 95% CI. The general average scores are close to the scores obtained in panel A with very small differences, differing only because some participant did not provide scores to some items. In all cases, our consumers' judgments of the durability of each category are very close to the Kuchler (2013) classification we used in our original analysis. This means that our estimates of the coefficient for the non-durability dummy / proportion are very close to those presented for the original Kuchler classification in the main text (in the main text, our results showed a coefficient for the non-durable dummy of 0.095 (Table 3.4, Column 3); while the results after the reclassification of merchant codes show a coefficient of 0.075 (Table B.7.1, Column 3))



How durable to you think these goods and services are?

Imagine you have just bought the goods and services below. For each item, state whether it is something that you typically use for a short period of time (something *non-durable*) or something that you continue using over a long period of time on many separate occasions (something *durable*).

Some of the items will be very difficult to rate, perhaps because you don't have enough information. Please do your best to answer these questions even if you feel you don't know enough. If you have truly no idea, you might click "4".

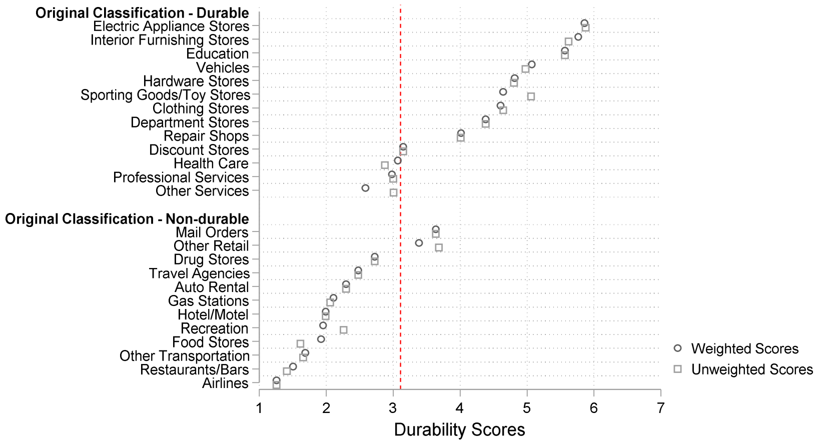
Please choose from the 1–7 scale, where:

- 1 on the scale means it is an item you typically consume over a **short period of time** (i.e., something that is *non-durable*), like an airline ticket
- 7 on the scale means it is an item you typically consume over a **long period of time or on many separate occasions** (i.e., something that is *durable*), like a car

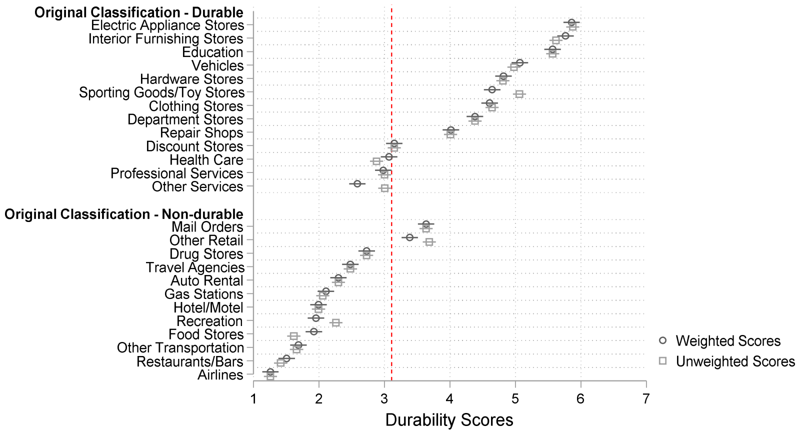
	Short Period of Time (Non-Durable)					Long Period of Time (Durable)
An Airline Ticket	1	2	3	4	5	6	7
A Car	1	2	3	4	5	6	7

Fig. B.7.1 Question format used in the consumer survey for the classification of items in durables and non-durables.

(A) Average durability scores for each merchant code



(B) Average durability scores for each merchant code computed within subject



(C) Normalized non-durability scores for each merchant code.

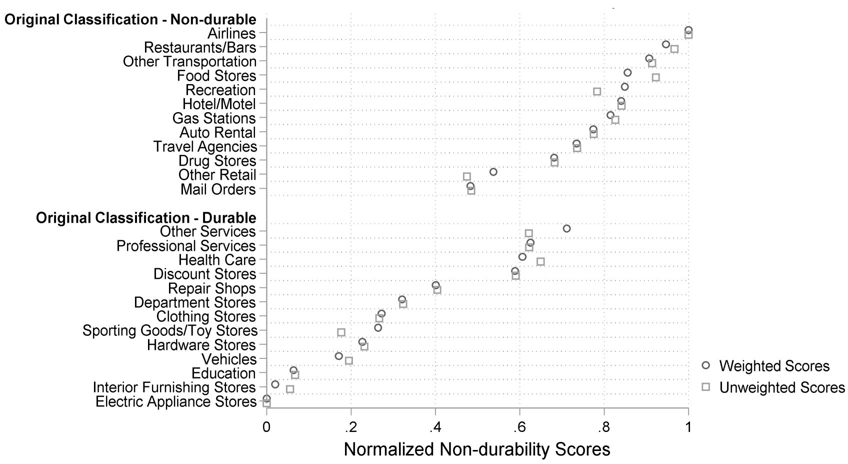


Fig. B.7.2 Durability scores for each merchant code. The red line highlights the median score. Lines span 95% confidence intervals.

Table B.7.1 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS – Quartile 1 (£5.02 - £54.69)	(5) OLS – Quartile 2 (Q2: £54.70 - £200.00)	(6) OLS – Quartile 3 (Q3: £200.01- £750.00)	(7) OLS – Quartile 4 (£750.01- £17000)
Non-durable = 1	0.0958***	0.0729***	0.0754***	0.0303***	0.102***	0.107***	0.0377***
	(0.00685)	(0.00569)	(0.00563)	(0.00924)	(0.0122)	(0.0133)	(0.00886)
Merchant APR (%)			0.00625***	0.00307***	0.00605***	0.00879***	0.00831***
			(0.000344)	(0.000515)	(0.000703)	(0.000834)	(0.000715)
Credit limit (£1000)			0.00252*	-0.000778	0.00354	0.00491	0.00321
			(0.00129)	(0.00219)	(0.00277)	(0.00333)	(0.00341)
Utilization (%)			-0.00156***	-0.00858**	-0.00352***	-0.00227***	-0.000700**
			(0.000218)	(0.00338)	(0.00130)	(0.000477)	(0.000328)
Account age (years)			0.128***	-0.00345	0.0941***	0.259***	0.321***
			(0.0124)	(0.0182)	(0.0252)	(0.0301)	(0.0245)
Amount purchase (£1000)		-1.073***	-0.953***	44.81	-125.6*	20.92	-0.215***
		(0.0161)	(0.0196)	(31.86)	(72.32)	(20.51)	(0.0533)
Amount purchase $(£1000)^2$		0.480***	0.439***	-3,223	2,129*	-116.9	0.0710***
		(0.0114)	(0.0117)	(2,770)	(1,294)	(98.93)	(0.0234)
Amount purchase $(£1000)^3$		-0.0864***	-0.0797***	109,502	-17,731	293.6	-0.0104**
		(0.00272)	(0.00273)	(108,277)	(11,089)	(228.5)	(0.00430)
Amount purchase $(£1000)^4$		0.00655***	0.00605***	$-1.819\text{x}10^{+06}$	71,726	-344.2	0.000691**
		(0.000251)	(0.000250)	$(1.944\text{x}10^{+06})$	(45,717)	(253.8)	(0.000337)
Amount purchase $(£1000)^5$		-0.000173***	-0.000160***	$1.167\text{x}10^{+07}$	-112,894	152.8	$-1.67\text{x}10^{-05}$*
		$(7.66\text{x}10^{-06})$	$(7.61\text{x}10^{-06})$	$(1.303\text{x}10^{+07})$	(72,759)	(108.7)	$(9.22\text{x}10^{-06})$
Constant	0.472***	0.778***	0.696***	0.613***	3.564**	-0.952	0.231***
	(0.00524)	(0.00543)	(0.0160)	(0.132)	(1.546)	(1.625)	(0.0455)
Observations	21,671	21,671	21,671	5,701	5,836	4,990	5,144
Observations Non-durable = 1	12,682	12,682	12,682	3,453	3,564	2,762	2,903
R-squared	0.009	0.322	0.341	0.023	0.065	0.099	0.108
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. The sample is restricted to new accounts and includes months in which purchases were related to only one merchant code. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £54.69. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.2 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £54.69)	OLS – Quartile 2 (Q2: £54.70 - £200.00)	OLS – Quartile 3 (Q3: £200.01- £750.00)	OLS – Quartile 4 (£750.01- £17000)
Non-durable = 1	0.0850***	0.0659***	0.0684***	0.0251**	0.0969***	0.0926***	0.0355***
	(0.00823)	(0.00687)	(0.00681)	(0.0105)	(0.0143)	(0.0165)	(0.0121)
Merchant APR (%)			0.00560***	0.00299***	0.00510***	0.00860***	0.00777***
			(0.000387)	(0.000571)	(0.000788)	(0.000953)	(0.000844)
Credit limit (£1000)			0.00168	0.000483	0.000818	0.00619	-0.00702
			(0.00152)	(0.00252)	(0.00318)	(0.00401)	(0.00453)
Utilization (%)			-0.00196***	-0.0109***	-0.00374**	-0.00236***	-0.00184***
			(0.000272)	(0.00398)	(0.00152)	(0.000579)	(0.000454)
Account age (years)			0.116***	-0.0193	0.100***	0.245***	0.294***
			(0.0147)	(0.0207)	(0.0294)	(0.0372)	(0.0311)
Amount purchase (£1000)		-1.088***	-0.954***	41.81	-95.44	20.17	-0.155*
		(0.0209)	(0.0251)	(35.63)	(85.30)	(25.31)	(0.0793)
Amount purchase $(£1000)^2$		0.499***	0.455***	-3,209	1,603	-114.2	0.0505
		(0.0156)	(0.0160)	(3,115)	(1,527)	(122.1)	(0.0362)
Amount purchase $(£1000)^3$		-0.0938***	-0.0864***	113,170	-13,216	289.1	-0.00668
		(0.00392)	(0.00393)	(122,394)	(13,098)	(282.4)	(0.00694)
Amount purchase $(£1000)^4$		0.00747***	0.00690***	$-1.876x10^{+06}$	52,723	-340.6	0.000407
		(0.000380)	(0.000379)	$(2.208x10^{+06})$	(54,039)	(313.7)	(0.000570)
Amount purchase $(£1000)^5$		-0.000208***	-0.000193***	$1.167x10^{+07}$	-81,694	151.6	$-9.45x10^{-06}$
		$(1.22x10^{-05})$	$(1.21x10^{-05})$	$(1.487x10^{+07})$	(86,072)	(134.5)	$(1.64x10^{-05})$
Median house price (£)	$1.24x10^{-07}$*	$3.05x10^{-08}$	$2.56x10^{-08}$	$-1.71x10^{-07}$**	$3.05x10^{-08}$	$5.35x10^{-08}$	$2.59x10^{-07}$**
	$(6.65x10^{-08})$	$(5.54x10^{-08})$	$(5.47x10^{-08})$	$(8.26x10^{-08})$	$(1.21x10^{-07})$	$(1.21x10^{-07})$	$(1.04x10^{-07})$
Free school meals (proportion)	-0.289***	-0.287***	-0.270***	-0.312***	-0.205*	-0.244*	-0.327***
	(0.0713)	(0.0594)	(0.0588)	(0.0910)	(0.121)	(0.144)	(0.105)
Weekly Household Income (£)	$-6.71x10^{-05}$	$-1.78x10^{-05}$	$-9.92x10^{-06}$	$-3.15x10^{-05}$	$5.60x10^{-05}$	$7.40x10^{-05}$	-0.000186**
	$(5.06x10^{-05})$	$(4.21x10^{-05})$	$(4.16x10^{-05})$	$(6.32x10^{-05})$	$(8.86x10^{-05})$	$(9.79x10^{-05})$	$(7.71x10^{-05})$
Constant	0.577***	0.846***	0.778***	0.734***	2.924	-0.853	0.430***
	(0.0348)	(0.0292)	(0.0341)	(0.153)	(1.822)	(2.006)	(0.0824)
Observations	14,851	14,851	14,851	4,262	4,099	3,341	3,149
Observations Non-durable = 1	8,687	8,687	8,687	2,559	2,485	1,853	1,790
R-squared	0.009	0.313	0.332	0.026	0.067	0.101	0.112
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.7.2 replicates Table B.7.1 specifications with the addition of socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to only one spending type. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £54.69. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.3 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £54.69)	OLS – Quartile 2 (Q2: £54.70 - £200.00)	OLS – Quartile 3 (Q3: £200.01- £750.00)	OLS – Quartile 4 (£750.01- £17000)
Non-durable (proportion)	0.149***	0.119***	0.118***	0.0253***	0.121***	0.190***	0.0853***
	(0.00498)	(0.00447)	(0.00441)	(0.00870)	(0.00944)	(0.00861)	(0.00730)
Merchant APR (%)			0.00703***	0.00317***	0.00608***	0.00818***	0.00794***
			(0.000250)	(0.000466)	(0.000475)	(0.000471)	(0.000576)
Credit limit (£1000)			0.00749***	-0.000653	0.00724***	0.0128***	0.00776***
			(0.000918)	(0.00200)	(0.00193)	(0.00172)	(0.00210)
Utilization (%)			-0.00206***	-0.00988***	-0.00248***	-0.00177***	-0.00161***
			(0.000140)	(0.00291)	(0.000780)	(0.000256)	(0.000223)
Account age (years)			0.142***	0.00282	0.0951***	0.192***	0.266***
			(0.00979)	(0.0166)	(0.0186)	(0.0193)	(0.0211)
Amount purchase (£1000)		-0.889***	-0.726***	61.03**	-101.3**	-13.63	-0.228***
		(0.0111)	(0.0132)	(29.91)	(51.02)	(10.58)	(0.0401)
Amount purchase (£1000)^2		0.406***	0.341***	-5,019*	1,624*	55.65	0.0691***
		(0.00820)	(0.00840)	(2,567)	(902.9)	(50.87)	(0.0190)
Amount purchase (£1000)^3		-0.0768***	-0.0648***	192,802*	-12,793*	-112.8	-0.00984***
		(0.00207)	(0.00208)	(99,206)	(7,667)	(117.2)	(0.00371)
Amount purchase (£1000)^4		0.00610***	0.00516***	-3.498x10^{+06}**	48,897	110.4	0.000661**
		(0.000201)	(0.000200)	(1.763x10^{+06})	(31,344)	(129.8)	(0.000306)
Amount purchase (£1000)^5		-0.000167***	-0.000142***	2.385x10^{+07}**	-72,566	-41.76	-1.66x10^{-05}*
		(6.37x10^{-06})	(6.32x10^{-06})	(1.170x10^{+07})	(49,535)	(55.53)	(8.72x10^{-06})
Constant	0.381***	0.709***	0.594***	0.563***	3.064***	1.597*	0.326***
	(0.00356)	(0.00433)	(0.0107)	(0.125)	(1.104)	(0.842)	(0.0316)
Observations	58,404	58,404	58,404	7,190	13,240	20,751	17,223
R-squared	0.015	0.214	0.240	0.023	0.054	0.083	0.083
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.7.3 replicates Table B.7.1 specifications for the months with both consumption types. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £54.69. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.4 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £54.69)	OLS – Quartile 2 (Q2: £54.70 - £200.00)	OLS – Quartile 3 (Q3: £200.01- £750.00)	OLS – Quartile 4 (£750.01- £17000)
Non-durable (proportion)	0.134***	0.106***	0.107***	0.0215**	0.113***	0.170***	0.0838***
	(0.00612)	(0.00546)	(0.00540)	(0.00990)	(0.0111)	(0.0108)	(0.00958)
Merchant APR (%)			0.00620***	0.00310***	0.00507***	0.00735***	0.00754***
			(0.000279)	(0.000517)	(0.000525)	(0.000530)	(0.000644)
Credit limit (£1000)			0.00588***	3.15×10^{-06}	0.00578***	0.0116***	0.00326
			(0.00110)	(0.00230)	(0.00223)	(0.00211)	(0.00267)
Utilization (%)			-0.00209***	-0.0120***	-0.00209**	-0.00172***	-0.00187***
			(0.000176)	(0.00341)	(0.000915)	(0.000321)	(0.000294)
Account age (years)			0.144***	-0.0151	0.103***	0.209***	0.287***
			(0.0116)	(0.0190)	(0.0214)	(0.0233)	(0.0260)
Amount purchase (£1000)		-0.922***	-0.759***	56.72*	-100.9*	-12.30	-0.220***
		(0.0143)	(0.0169)	(33.45)	(59.70)	(13.27)	(0.0567)
Amount purchase $(£1000)^2$		0.432***	0.366***	-4,865*	1,624	51.85	0.0692**
		(0.0110)	(0.0113)	(2,883)	(1,057)	(63.89)	(0.0276)
Amount purchase $(£1000)^3$		-0.0847***	-0.0723***	189,909*	-12,769	-110.3	-0.0103*
		(0.00290)	(0.00291)	(111,850)	(8,986)	(147.4)	(0.00557)
Amount purchase $(£1000)^4$		0.00703***	0.00601***	$-3.423 \times 10^{+06}$*	48,373	115.2	0.000727
		(0.000293)	(0.000292)	$(1.994 \times 10^{+06})$	(36,766)	(163.4)	(0.000477)
Amount purchase $(£1000)^5$		-0.000203***	-0.000174***	$2.293 \times 10^{+07}$*	-70,729	-47.24	-1.95×10^{-05}
		(9.71×10^{-06})	(9.65×10^{-06})	$(1.328 \times 10^{+07})$	(58,150)	(69.96)	(1.42×10^{-05})
Median house price (£)	1.77×10^{-07}***	1.12×10^{-07}***	9.96×10^{-08}***	-8.95×10^{-08}	1.22×10^{-07}	1.54×10^{-07}**	7.83×10^{-08}
	(4.00×10^{-08})	(3.56×10^{-08})	(3.51×10^{-08})	(7.59×10^{-08})	(7.76×10^{-08})	(6.14×10^{-08})	(6.20×10^{-08})
Free school meals (proportion)	-0.240***	-0.337***	-0.303***	-0.345***	-0.289***	-0.213***	-0.416***
	(0.0446)	(0.0397)	(0.0392)	(0.0812)	(0.0800)	(0.0732)	(0.0699)
Weekly Household Income (£)	-3.58×10^{-05}	4.26×10^{-05}	4.28×10^{-05}	-6.85×10^{-05}	2.48×10^{-06}	9.73×10^{-05}**	8.03×10^{-05}*
	(3.07×10^{-05})	(2.73×10^{-05})	(2.69×10^{-05})	(5.77×10^{-05})	(5.77×10^{-05})	(4.88×10^{-05})	(4.69×10^{-05})
Constant	0.447***	0.732***	0.619***	0.704***	3.062**	1.424	0.330***
	(0.0215)	(0.0194)	(0.0226)	(0.144)	(1.291)	(1.055)	(0.0539)
Observations	38,481	38,481	38,481	5,394	9,392	13,339	10,356
R-squared	0.015	0.221	0.244	0.026	0.056	0.084	0.098
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.7.4 replicates Table B.7.3 specifications but including socioeconomic controls: Median house price, proportion of students on free school meals and weekly household income. The sample is restricted to new accounts and includes months in which expenses were related to one or more purchase types. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchased amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £54.69. Quartiles cut-off values were defined based on the value of durable purchases. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.7.5 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable = 1	0.00532***	0.0139***	0.0185***	0.00420**	0.0123***	0.0166***	0.000869	0.00345*	0.00337*
	(0.00161)	(0.00158)	(0.00155)	(0.00194)	(0.00190)	(0.00187)	(0.00201)	(0.00200)	(0.00200)
Merchant APR (%)			0.0103***			0.00878***			0.00281***
			(0.000153)			(0.000187)			(0.000372)
Credit limit (£1000)			-0.00281***			-0.00253***			0.00636*
			(0.000379)			(0.000444)			(0.00357)
Utilization (%)			-0.00325***			-0.00335***			-0.000729***
			(9.50×10^{-05})			(0.000115)			(0.000156)
Account age (years)			0.00486***			0.00461***			-0.0111***
			(0.000138)			(0.000155)			(0.00171)
Amount purchase (£1000)		-0.368***	-0.222***		-0.358***	-0.218***		-0.148***	-0.122***
		(0.00540)	(0.00638)		(0.00643)	(0.00763)		(0.00740)	(0.00925)
Amount purchase $(£1000)^2$		0.116***	0.0879***		0.112***	0.0849***		0.0572***	0.0519***
		(0.00379)	(0.00376)		(0.00445)	(0.00445)		(0.00538)	(0.00551)
Amount purchase $(£1000)^3$		-0.0164***	-0.0134***		-0.0155***	-0.0125***		-0.00906***	-0.00846***
		(0.000850)	(0.000831)		(0.000981)	(0.000966)		(0.00124)	(0.00125)
Amount purchase $(£1000)^4$		0.00101***	0.000857***		0.000928***	0.000770***		0.000577***	0.000547***
		(7.14×10^{-05})	(6.95×10^{-05})		(8.08×10^{-05})	(7.93×10^{-05})		(0.000106)	(0.000107)
Amount purchase $(£1000)^5$		-2.21×10^{-05}***	-1.90×10^{-05}***		-1.95×10^{-05}***	-1.65×10^{-05}***		-1.25×10^{-05}***	-1.20×10^{-05}***
		(1.95×10^{-06})	(1.90×10^{-06})		(2.17×10^{-06})	(2.13×10^{-06})		(2.98×10^{-06})	(2.98×10^{-06})
Median house price (£)				1.24×10^{-08}	6.55×10^{-09}	-2.02×10^{-09}			
				(2.31×10^{-08})	(2.14×10^{-08})	(2.05×10^{-08})			
Free school meals (proportion)				-0.307***	-0.277***	-0.196***			
				(0.0269)	(0.0250)	(0.0240)			
Weekly Household Income (£)				-2.14×10^{-05}	-7.12×10^{-06}	6.82×10^{-06}			
				(1.77×10^{-05})	(1.65×10^{-05})	(1.58×10^{-05})			
Constant	0.801***	0.878***	0.700***	0.861***	0.921***	0.743***			
	(0.00153)	(0.00162)	(0.00399)	(0.0124)	(0.0115)	(0.0119)			
R-squared							0.000	0.014	0.016
Observations	154,924	154,924	154,924	107,384	107,384	107,384	93,957	93,957	93,957
Number of accounts	95,461	95,461	95,461	66,021	66,021	66,021	34,494	34,494	34,494
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. The sample includes all accounts and includes months in which expenses were related to only one merchant code. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Durable goods. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.6 Estimated Likelihood of Repaying Full Balance, Multiple-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durable (proportion)	0.0133***	0.0224***	0.0280***	0.0107***	0.0195***	0.0250***	0.00470***	0.00796***	0.00772***
	(0.00138)	(0.00136)	(0.00132)	(0.00165)	(0.00163)	(0.00159)	(0.00160)	(0.00159)	(0.00158)
Merchant APR (%)			0.0126***			0.0111***			0.00475***
			(0.000113)			(0.000137)			(0.000235)
Credit limit (£1000)			-0.00217***			-0.00235***			0.00954***
			(0.000335)			(0.000392)			(0.00236)
Utilization (%)			-0.00324***			-0.00330***			-0.000861***
			(6.69×10^{-05})			(8.18×10^{-05})			(0.000103)
Account age (years)			0.00659***			0.00627***			-0.00737***
			(0.000125)			(0.000141)			(0.00128)
Amount purchase (£1000)		-0.354***	-0.177***		-0.333***	-0.170***		-0.157***	-0.126***
		(0.00396)	(0.00458)		(0.00470)	(0.00549)		(0.00497)	(0.00612)
Amount purchase (£1000)^2		0.123***	0.0766***		0.112***	0.0707***		0.0653***	0.0583***
		(0.00291)	(0.00286)		(0.00340)	(0.00337)		(0.00379)	(0.00387)
Amount purchase (£1000)^3		-0.0193***	-0.0127***		-0.0169***	-0.0112***		-0.0114***	-0.0105***
		(0.000691)	(0.000668)		(0.000790)	(0.000771)		(0.000928)	(0.000932)
Amount purchase (£1000)^4		0.00130***	0.000876***		0.00110***	0.000742***		0.000798***	0.000743***
		(6.09×10^{-05})	(5.86×10^{-05})		(6.82×10^{-05})	(6.62×10^{-05})		(8.43×10^{-05})	(8.43×10^{-05})
Amount purchase (£1000)^5		-3.04×10^{-05}***	-2.08×10^{-05}***		-2.49×10^{-05}***	-1.70×10^{-05}***		-1.90×10^{-05}***	-1.78×10^{-05}***
		(1.73×10^{-06})	(1.66×10^{-06})		(1.90×10^{-06})	(1.84×10^{-06})		(2.47×10^{-06})	(2.47×10^{-06})
Median house price (£)				8.51×10^{-08}***	7.34×10^{-08}***	5.02×10^{-08}***			
				(1.97×10^{-08})	(1.83×10^{-08})	(1.71×10^{-08})			
Free school meals (proportion)				-0.367***	-0.358***	-0.230***			
				(0.0233)	(0.0216)	(0.0203)			
Weekly household income (£)				-4.99×10^{-05}***	-1.88×10^{-05}	1.39×10^{-05}			
				(1.53×10^{-05})	(1.42×10^{-05})	(1.33×10^{-05})			
Constant	0.718***	0.820***	0.614***	0.801***	0.872***	0.644***			
	(0.00133)	(0.00147)	(0.00312)	(0.0107)	(0.00999)	(0.00996)			
R-squared							0.000	0.017	0.021
Observations	282,997	282,997	282,997	194,214	194,214	194,214	184,673	184,673	184,673
Number of accounts	159,100	159,100	159,100	108,050	108,050	108,050	60,776	60,776	60,776
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note. Table B.7.6 replicates Table B.7.5 specifications but months with multiple consumption categories or merchant codes are added to the sample. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Reference category: Proportion of the total month spending on durable goods. Standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.7.7 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for New Accounts, Additional Controls

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS	OLS	OLS	OLS – Quartile 1 (£5.02 - £54.69)	OLS – Quartile 2 (Q2: £54.70 - £200.00)	OLS – Quartile 3 (Q3: £200.01- £750.00)	OLS – Quartile 4 (£750.01- £17000)
Non-durability Score (0 to 1)	0.307***	0.138***	0.142***	0.0420**	0.188***	0.159***	0.0827***
	(0.0137)	(0.0118)	(0.0116)	(0.0200)	(0.0255)	(0.0259)	(0.0194)
Merchant APR (%)			0.00559***	0.00297***	0.00514***	0.00862***	0.00774***
			(0.000386)	(0.000570)	(0.000787)	(0.000952)	(0.000843)
Credit limit (£1000)			0.00164	0.000414	0.000651	0.00604	-0.00679
			(0.00151)	(0.00252)	(0.00318)	(0.00401)	(0.00452)
Utilization (%)			-0.00197***	-0.0108***	-0.00380**	-0.00243***	-0.00181***
			(0.000272)	(0.00398)	(0.00151)	(0.000579)	(0.000453)
Account age (years)			0.116***	-0.0193	0.0997***	0.246***	0.292***
			(0.0147)	(0.0208)	(0.0294)	(0.0372)	(0.0311)
Amount purchase (£1000)		-1.058***	-0.923***	41.35	-95.54	23.02	-0.157**
		(0.0210)	(0.0252)	(35.64)	(85.21)	(25.29)	(0.0792)
Amount purchase $(£1000)^2$		0.483***	0.439***	-3,148	1,597	-127.6	0.0507
		(0.0156)	(0.0160)	(3,115)	(1,525)	(122.0)	(0.0362)
Amount purchase $(£1000)^3$		-0.0905***	-0.0830***	110,216	-13,109	319.3	-0.00665
		(0.00392)	(0.00394)	(122,393)	(13,084)	(282.1)	(0.00693)
Amount purchase $(£1000)^4$		0.00720***	0.00662***	$-1.815 \times 10^{+06}$	52,112	-373.4	0.000400
		(0.000381)	(0.000380)	$(2.208 \times 10^{+06})$	(53,982)	(313.4)	(0.000569)
Amount purchase $(£1000)^5$		-0.000200***	-0.000185***	$1.123 \times 10^{+07}$	-80,557	165.3	-9.22×10^{-06}
		(1.22×10^{-05})	(1.21×10^{-05})	$(1.486 \times 10^{+07})$	(85,982)	(134.4)	(1.64×10^{-05})
Median house price (£)	1.25×10^{-07}*	3.03×10^{-08}	2.52×10^{-08}	-1.73×10^{-07}**	3.59×10^{-08}	4.87×10^{-08}	2.65×10^{-07}**
	(6.57×10^{-08})	(5.53×10^{-08})	(5.46×10^{-08})	(8.26×10^{-08})	(1.21×10^{-07})	(1.21×10^{-07})	(1.04×10^{-07})
Free school meals (proportion)	-0.303***	-0.292***	-0.276***	-0.316***	-0.213*	-0.243*	-0.332***
	(0.0704)	(0.0593)	(0.0587)	(0.0910)	(0.121)	(0.144)	(0.104)
Weekly Household Income (£)	-8.50×10^{-05}*	-2.14×10^{-05}	-1.34×10^{-05}	-2.98×10^{-05}	4.83×10^{-05}	7.17×10^{-05}	-0.000193**
	(4.99×10^{-05})	(4.21×10^{-05})	(4.16×10^{-05})	(6.32×10^{-05})	(8.85×10^{-05})	(9.78×10^{-05})	(7.70×10^{-05})
Constant	0.464***	0.800***	0.734***	0.723***	2.886	-1.118	0.413***
	(0.0348)	(0.0296)	(0.0344)	(0.153)	(1.821)	(2.005)	(0.0824)
Observations	14,851	14,851	14,851	4,262	4,099	3,341	3,149
Observations Non-durable = 1	8,687	8,687	8,687	2,559	2,485	1,853	1,790
R-squared	0.034	0.315	0.334	0.026	0.069	0.103	0.114
Month FEs	NO	NO	YES	YES	YES	YES	YES

Note. Table B.7.7 replicates Table B.7.2 specifications but uses the normalized durability score instead of the dummy for durability. The sample is restricted to new accounts and includes months in which expenses were related to only one spending type. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 4 to 7 split the sample in 4 quartiles based on purchase amount. For instance, all purchases included in Model 4 had a monthly balance higher than £5.02 and up to £54.69. Quartiles cut-off values were defined based on the value of durable purchases. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.8 Estimated Likelihood of Repaying Full Balance, Single-Purchase-Type Sample for All Accounts

	RE			RE (+ socioeconomic controls)			FE		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-durability Score (0 to 1)	0.0599***	0.0373***	0.0436***	0.0570***	0.0345***	0.0407***	0.0174***	0.0106***	0.0104***
	(0.00293)	(0.00288)	(0.00282)	(0.00352)	(0.00346)	(0.00340)	(0.00365)	(0.00363)	(0.00363)
Merchant APR (%)			0.0103***			0.00877***			0.00281***
			(0.000153)			(0.000187)			(0.000372)
Credit limit (£1000)			-0.00283***			-0.00253***			0.00640*
			(0.000379)			(0.000444)			(0.00357)
Utilization (%)			-0.00324***			-0.00335***			-0.000727***
			(9.49x10^{-05})			(0.000115)			(0.000156)
Account age (years)			0.00488***			0.00464***			-0.0111***
			(0.000137)			(0.000155)			(0.00171)
Amount purchase (£1000)		-0.361***	-0.214***		-0.352***	-0.210***		-0.146***	-0.120***
		(0.00541)	(0.00638)		(0.00644)	(0.00764)		(0.00741)	(0.00926)
Amount purchase (£1000)^2		0.113***	0.0837***		0.109***	0.0810***		0.0562***	0.0509***
		(0.00379)	(0.00377)		(0.00446)	(0.00446)		(0.00539)	(0.00551)
Amount purchase (£1000)^3		-0.0158***	-0.0127***		-0.0150***	-0.0118***		-0.00888***	-0.00829***
		(0.000851)	(0.000832)		(0.000982)	(0.000967)		(0.00124)	(0.00125)
Amount purchase (£1000)^4		0.000970***	0.000805***		0.000888***	0.000722***		0.000565***	0.000535***
		(7.15x10^{-05})	(6.95x10^{-05})		(8.09x10^{-05})	(7.93x10^{-05})		(0.000106)	(0.000107)
Amount purchase (£1000)^5		-2.11x10^{-05}***	-1.78x10^{-05}***		-1.86x10^{-05}***	-1.54x10^{-05}***		-1.22x10^{-05}***	-1.17x10^{-05}***
		(1.95x10^{-06})	(1.90x10^{-06})		(2.17x10^{-06})	(2.13x10^{-06})		(2.98x10^{-06})	(2.98x10^{-06})
Median house price (£)				1.09x10^{-08}	5.96x10^{-09}	-2.67x10^{-09}			
				(2.30x10^{-08})	(2.14x10^{-08})	(2.05x10^{-08})			
Free school meals (proportion)				-0.310***	-0.278***	-0.197***			
				(0.0269)	(0.0250)	(0.0240)			
Weekly Household Income (£)				-2.47x10^{-05}	-8.33x10^{-06}	5.59x10^{-06}			
				(1.77x10^{-05})	(1.65x10^{-05})	(1.58x10^{-05})			
Constant	0.770***	0.863***	0.683***	0.833***	0.908***	0.728***			
	(0.00211)	(0.00223)	(0.00426)	(0.0125)	(0.0117)	(0.0120)			
R-squared							0.000	0.014	0.016
Observations	154,924	154,924	154,924	107,384	107,384	107,384	93,957	93,957	93,957
Number of accounts	95,461	95,461	95,461	66,021	66,021	66,021	34,494	34,494	34,494
Month FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES

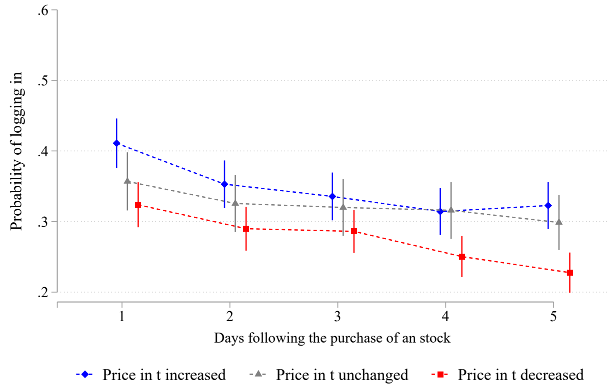
Note. Table B.7.8 replicates Table B.7.5 specifications but uses the normalized durability score instead of the dummy for durability. The sample includes all accounts and includes months in which expenses were related to only one merchant code. All models are linear probability models in which the outcome takes the value of one when the repayment-purchase ratio is greater than .9 and otherwise takes a value of zero. Models 1 to 6 are RE models, while Models 7 to 9 are FE models that control for unobserved account heterogeneity. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix C

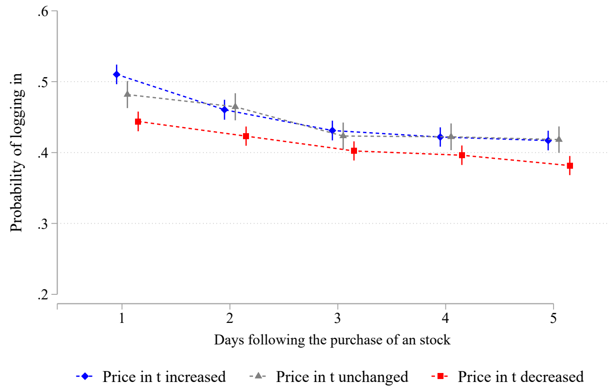
You Only Watch When You're Winning: Selective Attention Among Individual Investors

C.1 Selective Attention I: Stock Prices and Login Behaviour

(A) Increase position in the only stock present in the portfolio



(B) Buy a new stock, portfolio has other stocks



(C) Increase position in one stock, portfolio has other stocks

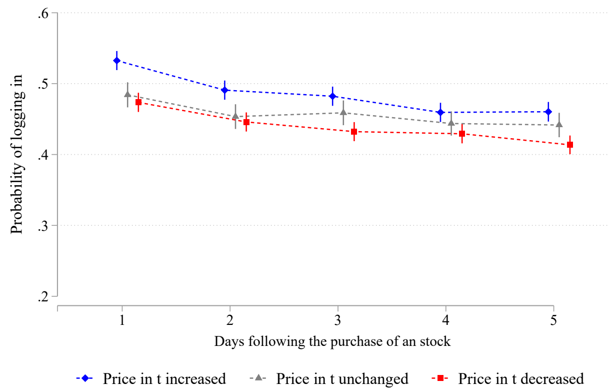
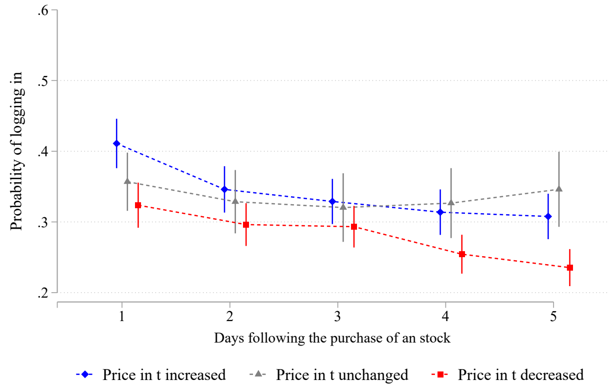
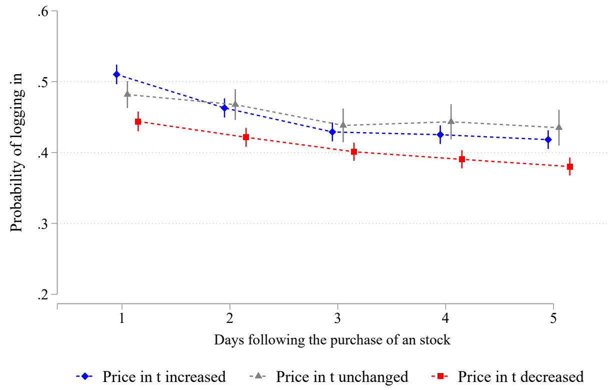


Fig. C.1.1 Probability of logging in by price change of most recent purchased stock, daily price changes.The panels shows the raw likelihood of logging in during the 5 business days following the purchase of an stock, excluding bank holidays, according to changes in the daily return of that stock. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (2,119 weeks from 1,023 accounts), (B) has a portfolio of stocks and buys a new stock (12,566 weeks from 5,313 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (13,600 weeks from 4,339 accounts). The latter case of accounts x weeks (C) includes the first group of accounts x weeks (A). In all weeks, no other transaction has taken place. Lines span 95% confidence intervals.

(A) Increase position in the only stock present in the portfolio



(B) Buy a new stock, portfolio has other stocks



(C) Increase position in one stock, portfolio has other stocks

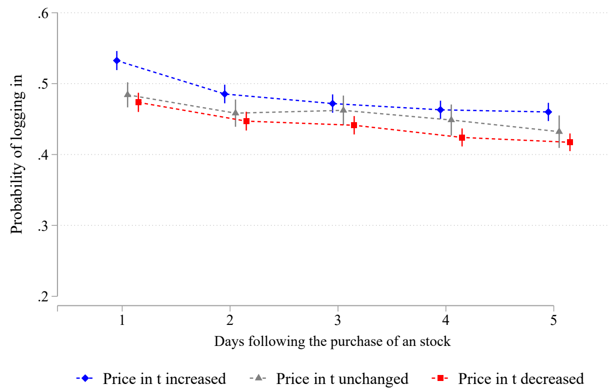
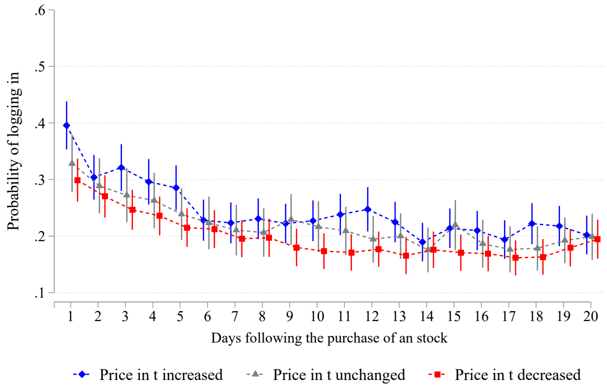
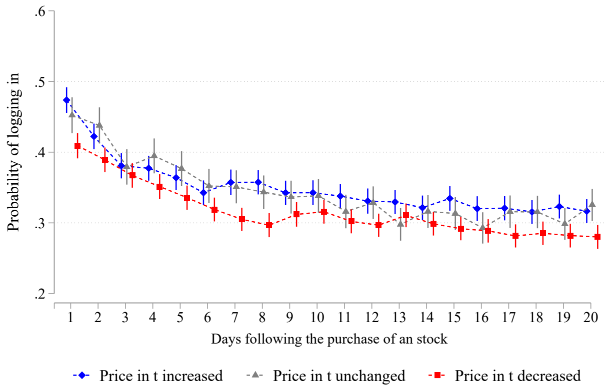


Fig. C.1.2 Probability of logging in by price change of most recent purchased stock, price changes since purchase. The panels shows the raw likelihood of logging in during the 5 business days following the purchase of an stock, excluding bank holidays, according to changes in the return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (2,119 weeks from 1,023 accounts), (B) has a portfolio of stocks and buys a new stock (12,566 weeks from 5,313 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (13,600 weeks from 4,339 accounts). The latter case of accounts x weeks (C) includes the first group of accounts x weeks (A). In all weeks, no other transaction has taken place. Lines span 95% confidence intervals.

(A) Increase position in the only stock present in the portfolio



(B) Buy a new stock, but have already a portfolio with other stocks



(C) Increase position in one stock, but have already a portfolio with other stocks

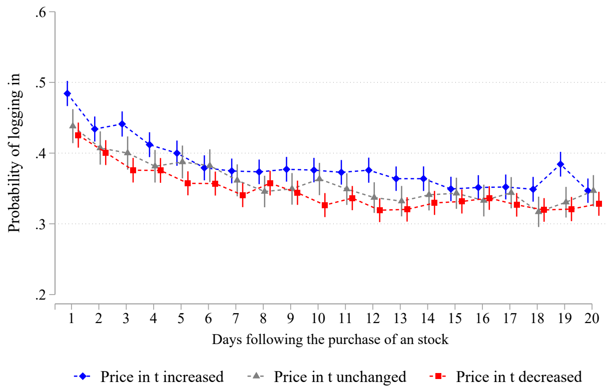
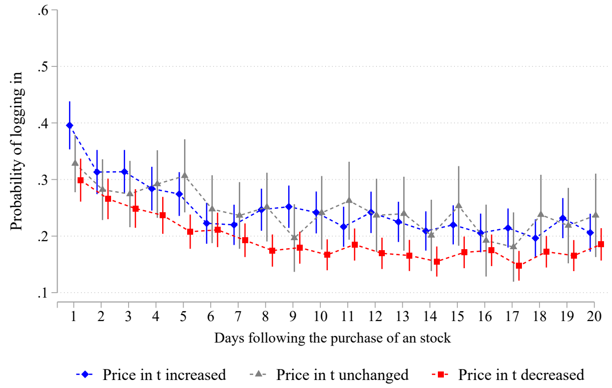
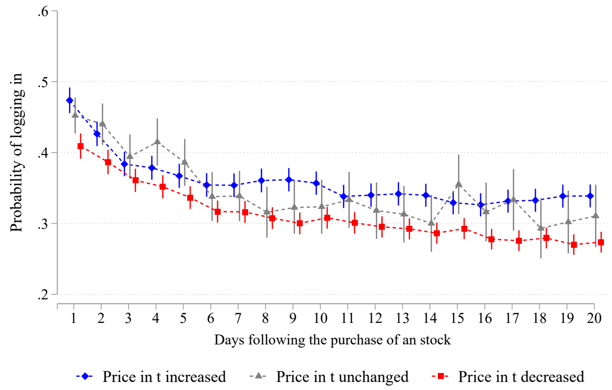


Fig. C.1.3 Probability of logging in by price changes of most recent purchased stock, price changes since purchase, one month window. The panels shows the raw likelihood of logging in during the 20 business days following the purchase of an stock, excluding bank holidays, according to changes in the daily return of that stock. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (1,407 months from 828 accounts), (B) has a portfolio of stocks and buys a new stock (7,300 months from 4,200 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (7,668 months from 3,570 accounts). The latter case of accounts x months (C) includes the first group of accounts x months (A). In all months, no other transaction has taken place. Lines span 95% confidence intervals.

(A) Increase position in the only stock present in the portfolio



(B) Buy a new stock, but have already a portfolio with other stocks



(C) Increase position in one stock, but have already a portfolio with other stocks

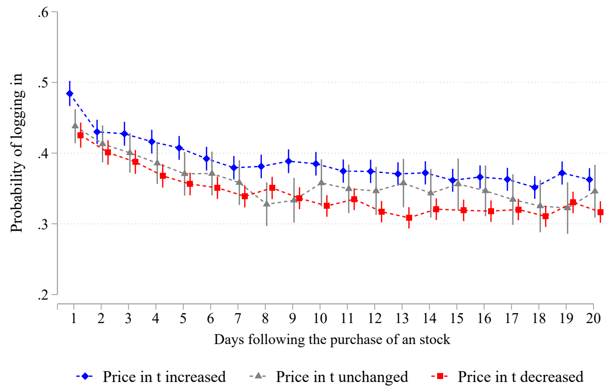


Fig. C.1.4 Probability of logging in by return of most recent purchased stock, return day t vs. day 0, across one month. The panels shows the raw likelihood of logging in during the 20 business days following the purchase of an stock, excluding bank holidays, according to changes in the return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (1,407 months from 828 accounts), (B) has a portfolio of stocks and buys a new stock (7,300 months from 4,200 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (7,668 months from 3,570 accounts). The latter case of accounts x months (C) includes the first group of accounts x months (A). In all months, no other transaction has taken place. Lines span 95% confidence intervals.

Table C.1.1 Logins and Daily Returns, by Stock Seniority, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock + (Daily)	0.008***	0.002	0.005*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Purchased Stock - (Daily)	0.002	0.008***	0.003	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Second Stock + (Daily)	0.004	0.006**	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Second Stock - (Daily)	0.002	0.009***	0.009***	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
% Change, Remaining Stocks + (Daily)	0.007*	0.005	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
% Change, Remaining Stocks - (Daily)	0.014***	0.008*	0.010***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Female=1	-0.010	-0.018	-0.001	-0.006
	(0.015)	(0.015)	(0.015)	(0.015)
Investor Age				
28 - 37 years old	-0.048	-0.051	-0.069	-0.087**
	(0.037)	(0.036)	(0.037)	(0.037)
38 - 47 years old	0.006	0.001	-0.004	-0.008
	(0.036)	(0.035)	(0.037)	(0.036)
48 - 57 years old	-0.006	-0.012	-0.018	-0.018
	(0.035)	(0.035)	(0.036)	(0.036)
58 - 67 years old	0.025	0.021	0.013	0.009
	(0.036)	(0.036)	(0.037)	(0.037)
68 or more years old	0.059	0.059	0.059	0.059
	(0.037)	(0.037)	(0.038)	(0.038)
Number of Trade Days per Month				
Quartile 2	0.091***	0.099***	0.108***	0.091***
	(0.020)	(0.018)	(0.018)	(0.018)
Quartile 3	0.198***	0.203***	0.203***	0.198***
	(0.019)	(0.018)	(0.017)	(0.017)
Quartile 4	0.341***	0.347***	0.340***	0.336***
	(0.019)	(0.018)	(0.018)	(0.018)
Portfolio Value				
Quartile 2	-0.007	0.009	0.007	0.011
	(0.024)	(0.023)	(0.023)	(0.024)
Quartile 3	0.014	0.024	0.027	0.028
	(0.024)	(0.022)	(0.023)	(0.023)
Quartile 4	0.017	0.038	0.034	0.032
	(0.025)	(0.024)	(0.024)	(0.024)
Number of Stocks				
Quartile 2	-0.151***	-0.162***	-0.146***	-0.126**
	(0.049)	(0.047)	(0.054)	(0.052)
Quartile 3	-0.129***	-0.133***	-0.117*	-0.086
	(0.048)	(0.047)	(0.054)	(0.051)
Quartile 4	-0.155***	-0.150***	-0.137**	-0.103*
	(0.049)	(0.048)	(0.055)	(0.052)
Constant	0.437***	0.418***	0.400***	0.371***
	(0.105)	(0.110)	(0.097)	(0.094)
Observations	44090	44090	44090	44085
Number of Accounts	3648	3648	3648	3648
Adjusted R-squared	0.0599	0.0669	0.0643	0.0687
Region FE	Yes	Yes	Yes	Yes

Note. The table replicates Table 4.8 but distinguishing the effect of changes in prices of the most recent stock and the second recent stock. The data is therefore restricted to months in which the cardholders has a portfolio of at least three stocks after the purchase day. Change in value of the purchased stock is computed daily with respect of the value in the preceding business day. Change in value followed by a positive sign records the changes from 0; while change in value followed by a negative sign, up to 0 (excluding 0). The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Standard errors in parentheses. Significance levels: Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

Table C.1.2 Logins and Returns Since Purchase, by Stock Seniority, OLS Model Estimates

	(1)	(2)	(3)	(4)
% Change, Purchased Stock + (Since Purchase)	0.002	0.002	-0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
% Change, Purchased Stock - (Since Purchase)	0.004*	0.003*	0.004***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
% Change, Second Stock + (Since Purchase)	-0.001	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
% Change, Second Stock - (Since Purchase)	0.003	0.002	0.002*	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
% Change, Remaining Stocks + (Since Purchase)	0.000	0.002	0.003	0.003*
	(0.003)	(0.002)	(0.002)	(0.001)
% Change, Remaining Stocks - (Since Purchase)	0.012***	0.006***	0.005***	0.004***
	(0.003)	(0.002)	(0.002)	(0.001)
Female=1	-0.011	-0.017	-0.001	-0.005
	(0.015)	(0.015)	(0.015)	(0.015)
Investor Age				
28 - 37 years old	-0.047	-0.052	-0.069	-0.089**
	(0.037)	(0.036)	(0.037)	(0.037)
38 - 47 years old	0.006	0.002	-0.003	-0.009
	(0.036)	(0.036)	(0.037)	(0.037)
48 - 57 years old	-0.005	-0.012	-0.017	-0.018
	(0.035)	(0.035)	(0.036)	(0.036)
58 - 67 years old	0.026	0.021	0.015	0.009
	(0.036)	(0.036)	(0.037)	(0.037)
68 or more years old	0.060	0.060	0.061	0.059
	(0.037)	(0.037)	(0.039)	(0.038)
Number of Trade Days per Month				
Quartile 2	0.093***	0.100***	0.109***	0.091***
	(0.020)	(0.018)	(0.018)	(0.018)
Quartile 3	0.200***	0.204***	0.204***	0.199***
	(0.019)	(0.018)	(0.017)	(0.017)
Quartile 4	0.344***	0.348***	0.343***	0.338***
	(0.019)	(0.018)	(0.018)	(0.018)
Portfolio Value				
Quartile 2	-0.008	0.008	0.004	0.008
	(0.024)	(0.023)	(0.023)	(0.024)
Quartile 3	0.011	0.023	0.024	0.024
	(0.024)	(0.022)	(0.023)	(0.023)
Quartile 4	0.012	0.033	0.027	0.025
	(0.024)	(0.024)	(0.024)	(0.024)
Number of Stocks				
Quartile 2	-0.155***	-0.170***	-0.155***	-0.135***
	(0.049)	(0.047)	(0.054)	(0.052)
Quartile 3	-0.135***	-0.142***	-0.127**	-0.095
	(0.048)	(0.046)	(0.053)	(0.051)
Quartile 4	-0.162***	-0.160***	-0.147***	-0.112*
	(0.049)	(0.047)	(0.054)	(0.052)
Constant	0.460***	0.434***	0.426***	0.391***
	(0.106)	(0.111)	(0.099)	(0.096)
Observations	44090	44090	44090	44085
Number of Accounts	3648	3648	3648	3648
Adjusted R-squared	0.0605	0.0675	0.0662	0.0714
Region FE	Yes	Yes	Yes	Yes

Note. The table replicates Table 4.9 but distinguishing the effect of changes in prices of the most recent stock and the second recent stock. The data is therefore restricted to months in which the cardholders has a portfolio of at least three stocks after the purchase day. Change in value of the purchased stock is computed daily with respect of the value at the end of the purchase day. Change in value of the rest of the portfolio are measured with respect of the value during that day too. Change in value followed by a positive sign records the changes from 0; while change in value followed by a negative sign, up to 0 (excluding 0). The other regressors, monthly frequency of trades, portfolio value and number of stocks, reflect account average measures. Standard errors in parentheses. Significance levels: *** $p<0.01$,** $p<0.02$, * $p<0.05$.

C.2 Selective Attention II: Evidence from Weather Shocks

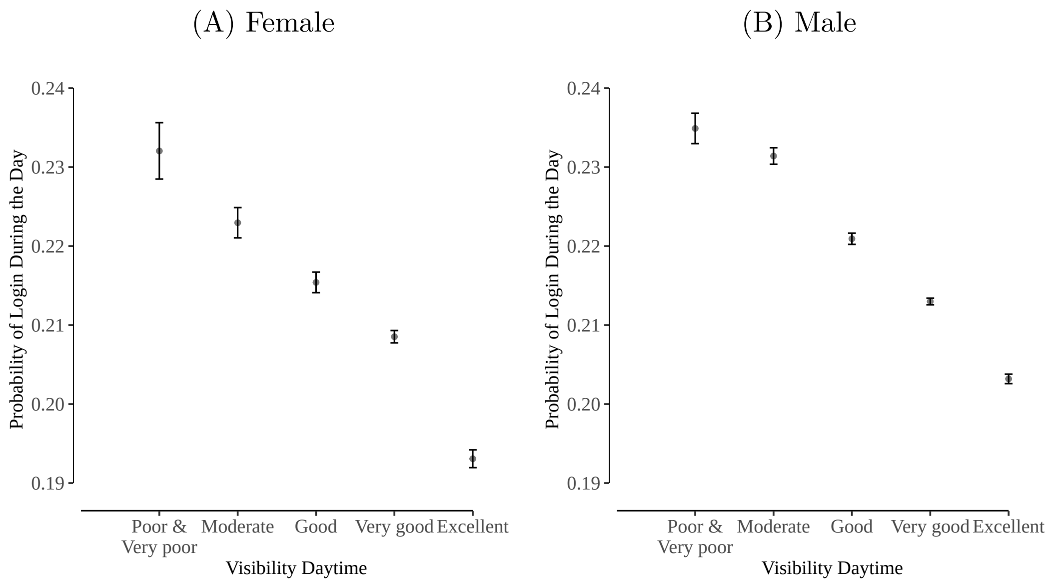
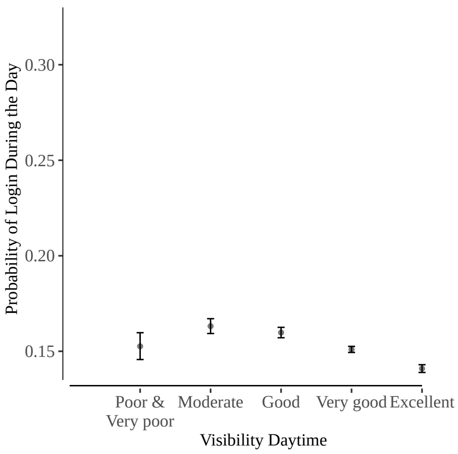
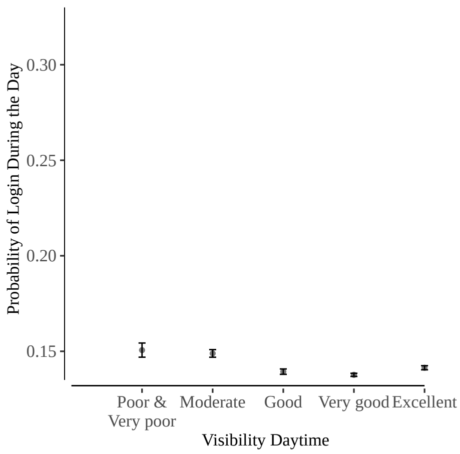


Fig. C.2.1 Probability of logging in by gender and daytime visibility. lines span 95% confidence intervals.

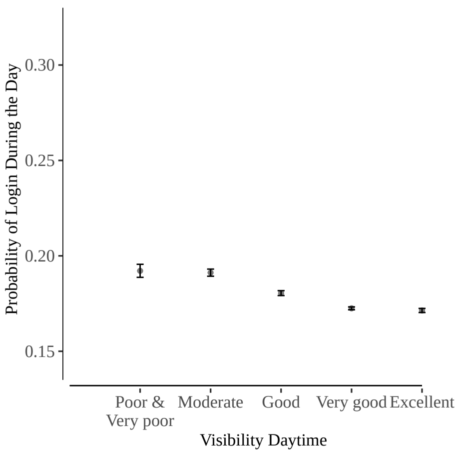
(A) 27 or less years old



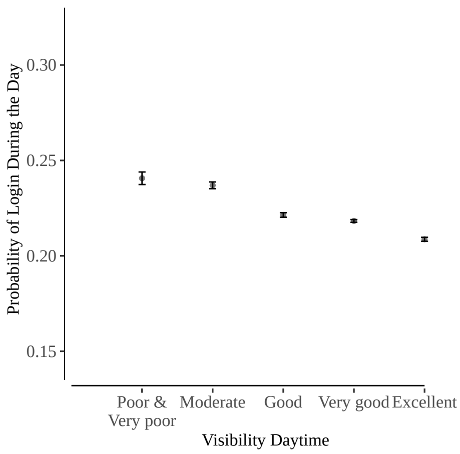
(B) 28 - 37 years old



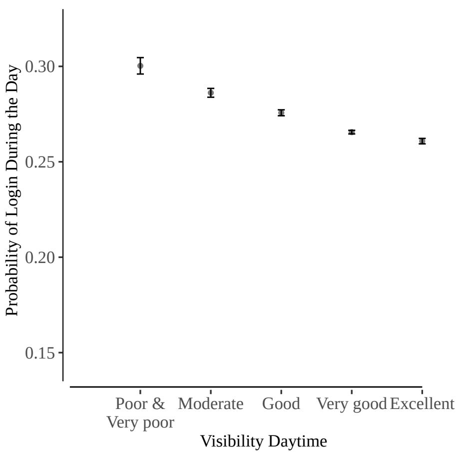
(C) 38 - 47 years old



(D) 48 - 57 years old



(E) 58 - 67 years old



(F) 68 or more years old

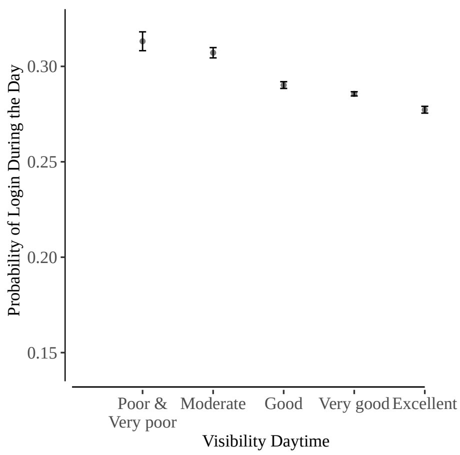


Fig. C.2.2 Probability of logging in by investor age and daytime visibility. lines span 95% confidence intervals.

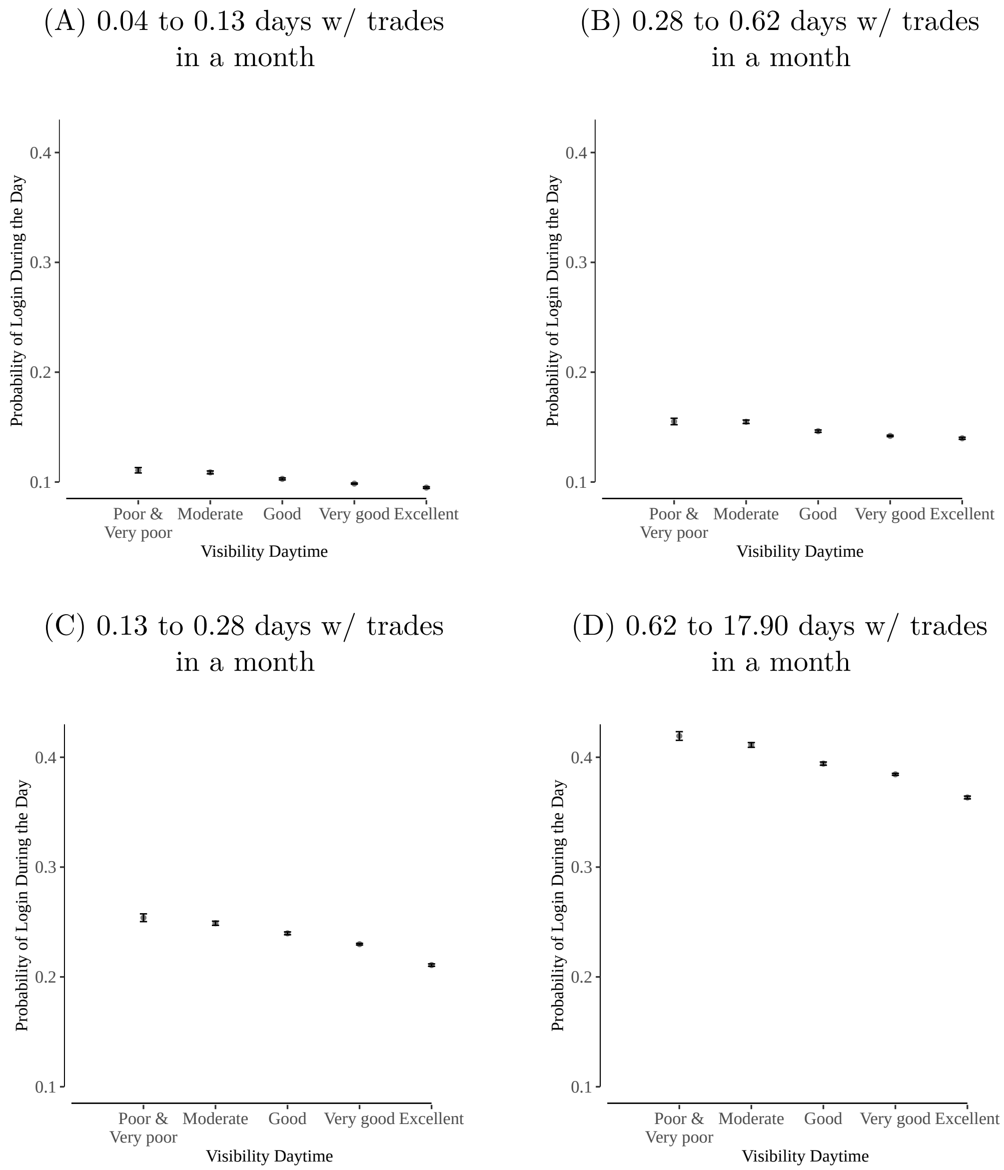


Fig. C.2.3 Probability of logging in by investor experience and daytime visibility. Lines span 95% confidence intervals.

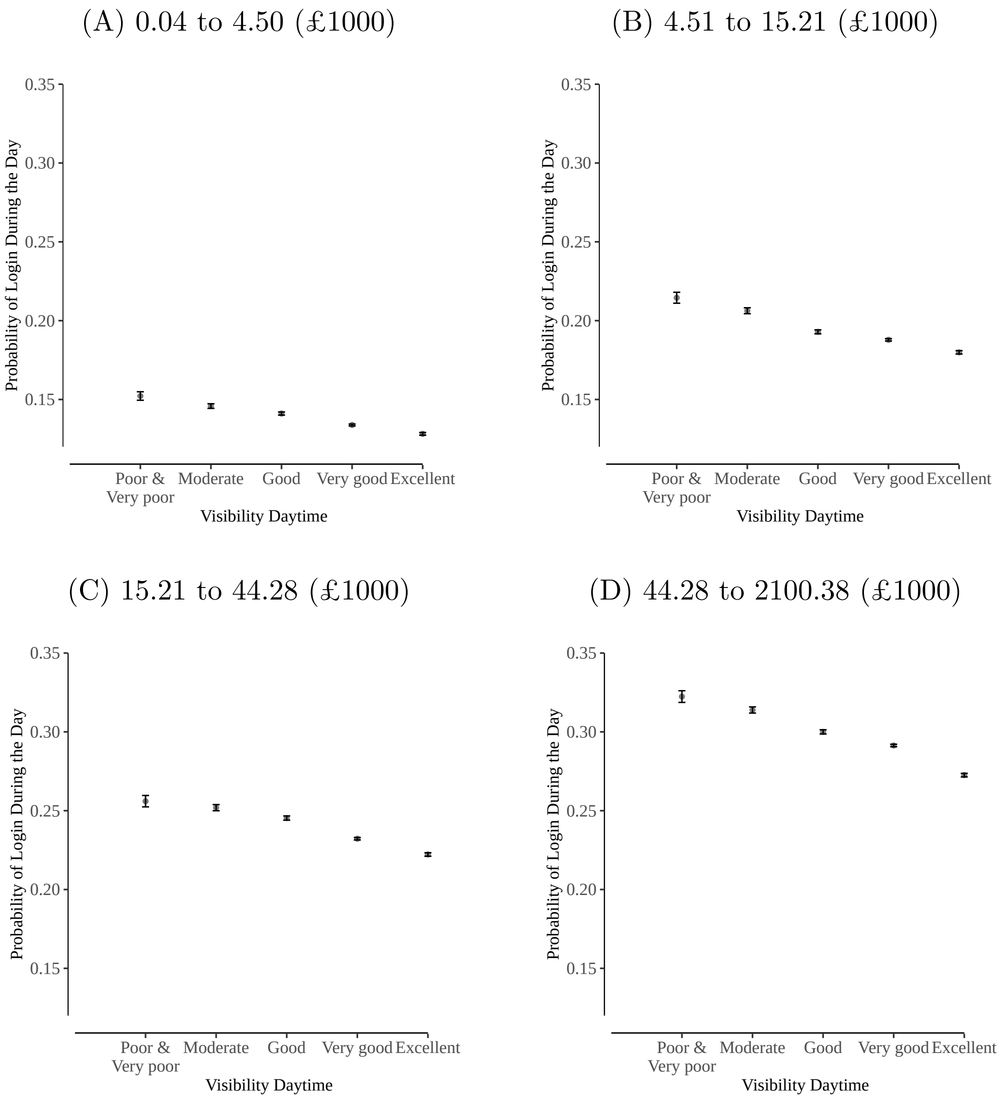


Fig. C.2.4 Probability of logging in by investor portfolio value and daytime visibility. The plot shows the variation in login rates conditional on the portfolio value at the beginning of the month. Lines span 95% confidence intervals.

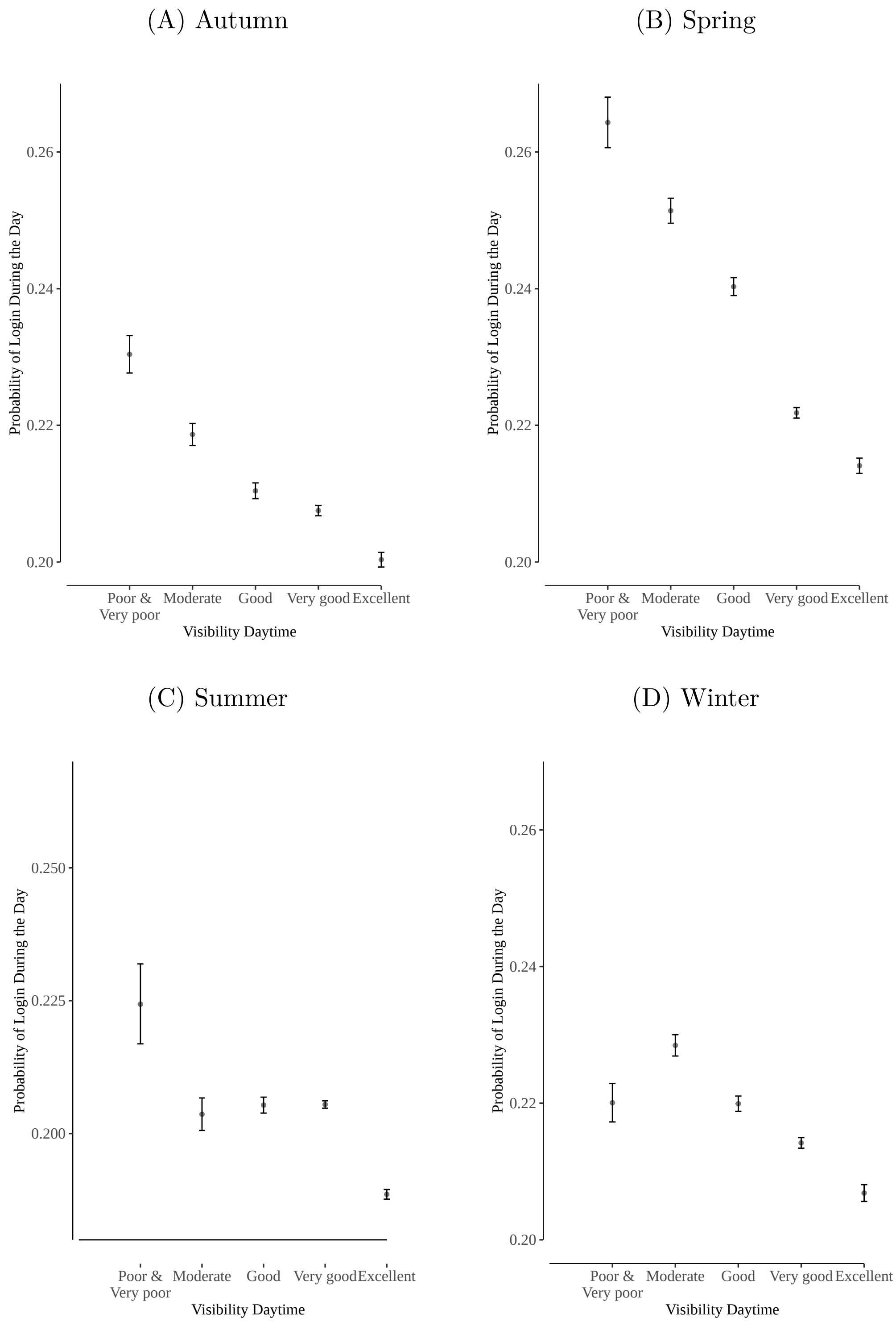


Fig. C.2.5 Probability of logging in by season and daytime visibility. Lines span 95% confidence intervals.